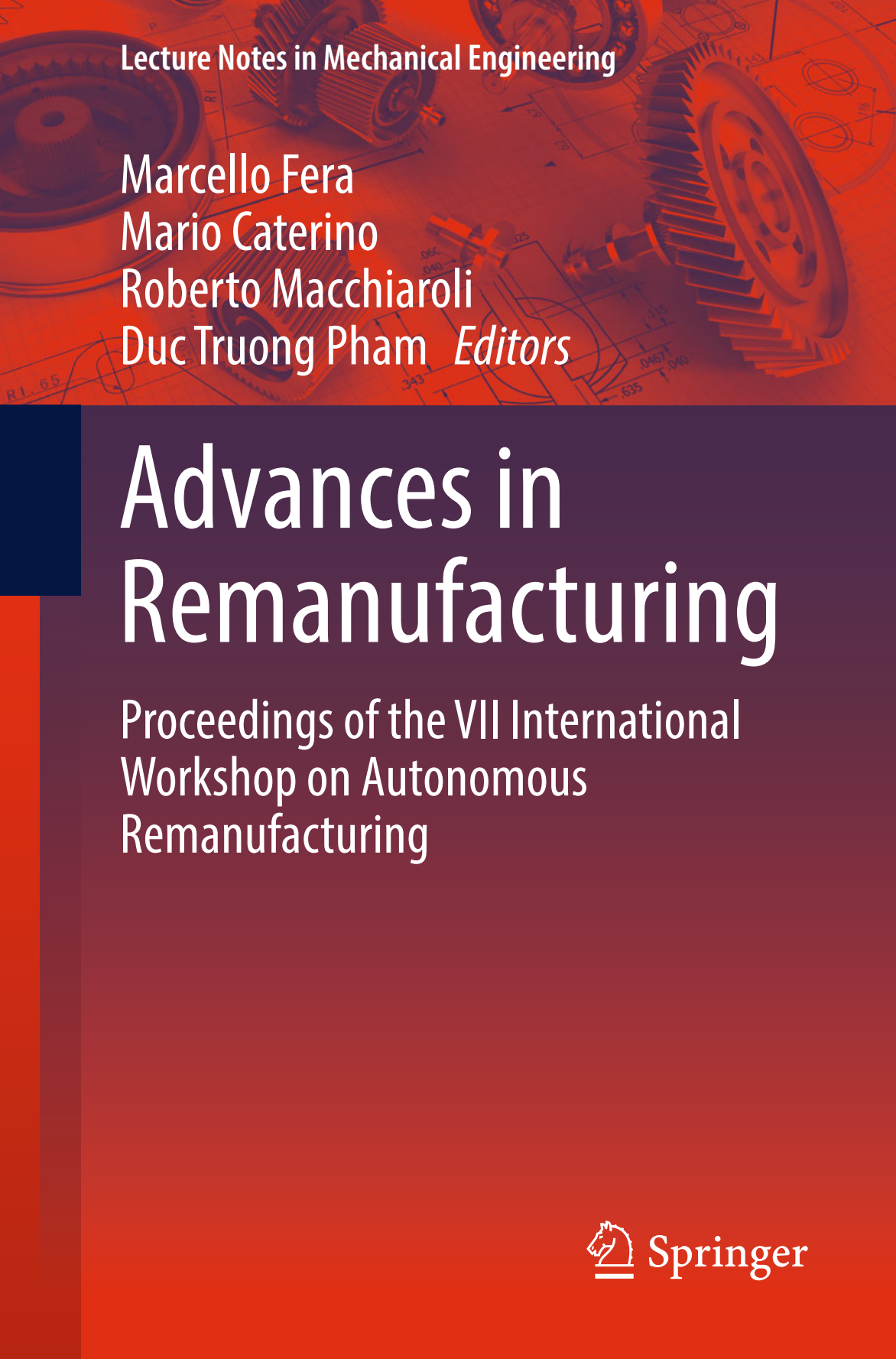




Lecture Notes in Mechanical Engineering

Marcello Fera
Mario Caterino
Roberto Macchiaroli
Duc Truong Pham *Editors*

Advances in Remanufacturing

Proceedings of the VII International
Workshop on Autonomous
Remanufacturing

Lecture Notes in Mechanical Engineering

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Marcello Fera
Department of Engineering
University of Campania Luigi Vanvitelli
Aversa, Italy

Roberto Macchiaroli
Department of Engineering
University of Campania Luigi Vanvitelli
Aversa, Italy

Mario Caterino
Department of Industrial Engineering
University of Salerno
Fisciano, Italy

Duc Truong Pham
Department of Mechanical Engineering
The University of Birmingham
Birmingham, UK

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Preface

Climate change, excessive waste generation and scarcity of natural resources are among the key factors that require the world to move towards the concept of sustainability. In this context, the production and manufacturing systems are challenged to adapt their processes to reduce the impact on the planet. A solution is represented by the realisation of circular economy models, which, in contrast to linear models, enable the reuse of resources, reducing waste and emissions. Remanufacturing represents an effective way to achieve circular models and, for this reason, is experiencing strong growth. Remanufacturing is the process that restores used products to “common operating and aesthetic standards”, contributing to saving resources considering both financial and environmental perspectives. However, the remanufacturing process may be very difficult to manage because of the many uncertainties affecting the quality of the used products and the still scarce knowledge on this topic.

This book collects chapters dedicated to enhancing remanufacturing processes, by discussing how modern technologies and new models integrating them may represent a great boost in this sector. The research associated with the chapters has been presented at the VII International Workshop on Autonomous Remanufacturing, held in October 2023 at the University of Campania Luigi Vanvitelli, in Italy.

The book opens with recent studies to assess the state of the art on different remanufacturing aspects. The development of sustainable remanufacturing systems is analysed in Chapter “[Development of Sustainable Remanufacturing Systems: Literature Review](#)”; the use of modern technologies, such as artificial intelligence, robotics and simulation, is assessed in Chapters “[Artificial Intelligence in Remanufacturing Contexts: Current Status and Future Opportunities](#)”—“[The Role of Simulation-Based Optimization in Remanufacturing and Reverse Logistics: A Systematic Literature Review](#)”; Chapter “[Exploring Industry 5.0 for Remanufacturing of Lithium-Ion Batteries in Electric Vehicles](#)” explores the use of Industry 4.0 concepts and technologies in remanufacturing; Chapter “[Remanufacturing Decision-Making Tools: A State of the Art](#)” highlights the use of decision support systems in remanufacturing;

and, finally, Chapter “[Consumer Acceptance and Preferences Based on Environment Knowledge to Inform Remanufacturing End-of-Life Approach for Electric Vehicle Battery: A Scoping Review Study](#)” assesses consumers’ acceptance and preferences for remanufactured electric vehicle batteries.

The second part of the book includes chapters highlighting the benefits brought to remanufacturing by modern technologies, typical of the Industry 4.0 paradigm, including automation, artificial intelligence and the Industrial Internet of Things. This part is composed of 16 chapters. Chapters “[Integration of Augmented Reality and Digital Twins in a Teleoperated Disassembly System](#)”–“[Exploring in the Application Slicing Technology to Determine Spatial Information to Assist and Facilitate Robotic Disassembly](#)” discuss the use of robotics in remanufacturing. According to these chapters, the collaboration between humans and robots represents an effective solution for the disassembly process. Moreover, combining Human-Robot Collaboration (HRC) with other technologies, such as Digital Twin (DT) or Augmented Reality (AR), helps to further improve the overall process, by also guaranteeing adequate safety within the working environment. Chapters “[Image-Based Incremental Learning for Part Recognition of Used Automotive Cores in Reverse Logistics](#)”–“[Knowledge Graph-Driven Manufacturing Resources Recommendation Method for Ship Pipe Manufacturing Workshop](#)” discuss the use of Artificial Intelligence (AI) systems in remanufacturing. Different machine learning approaches are used for parts recognition, to evaluate the quality of returned cores, to estimate their remaining useful life or to identify defects that may compromise the goodness of the remanufacturing process. Finally, Chapters “[Digital Twin-driven Dynamic Scheduling Cloud Platform for Disassembly Workshop](#)”–“[Knowledge-Driven Scheduling of Digital Twin-Based Flexible Ship Pipe Manufacturing Workshop](#)” discuss the use of digital twins and the Industrial Internet of Things (IIoT) for the scheduling of remanufacturing activities.

The third part of the book discusses the remanufacturing strategy as an enabler of circular economy concepts. Nine chapters are included in this part. Chapter “[Impact of Incentive Policies on the Profitability of Manufacturers and Third-Party Remanufacturers in the Circular Economy](#)” discusses the impact of incentive policies on the profitability of remanufacturers; Chapters “[Analysis of Strategies and Models for Industrial Symbiosis in Manufacturing Ecosystems](#)” and “[Assessing the Impact of Remanufacturing Through Industrial Symbiosis on Supply Chain Performance](#)” address industrial symbiosis as a driver to reduce waste, which is also the main objective of the proposal of Chapter “[Manufacture of a New Sustainable Material from Bacterial Cellulose from Organic Waste in a Circular Economy Framework](#)”, through the production of a new material obtained from waste; Chapter “[Circular Economy and Autonomous Remanufacturing for End-of-Life Offshore Wind Turbines](#)” discusses the remanufacturing of offshore wind turbines to promote circular economy; Chapters “[Industry 4.0 Support of Remanufacturing Operations](#)”–“[Science Mapping Analysis for the Development of a Remanufacturing Readiness Model](#)” discuss the impact of remanufacturing on circularity by proposing new methodologies, using frameworks, readiness models and life cycle cost analysis.

The fourth and last part of the book introduces new methods for improving three crucial aspects of remanufacturing: the design of products to be remanufactured, in Chapters “Tools and Methods for Designing Mechanical Components for Multiple Remanufacturing Cycles in Agricultural Machinery”–Product Design Evaluation of Refrigerators to Facilitate Remanufacturing Process; the disassembly process, in Chapters Modelling Remanufacturing Process of End-of-Life Batteries Using Discrete Event Simulation–“Disassembly Strategies for Remanufacturing: Experiences from a Learning Factory”; and the repairing of damaged components, in chapters RE-AM Combined Use to Facilitate Decision-Making in Remanufacturing–“Integrating Remanufactured and 3D Parts in Asset Maintenance Improvement”.

In realising this book and the associated workshop, we aimed to demonstrate how remanufacturing is gaining even more attention all over the world, a clear sign that the focus on sustainability and the circular economy is intensifying. This book also demonstrates that there is much room for improvement in the remanufacturing sector and that research represents the base to reach it.

Aversa, Italy
Fisciano, Italy
Aversa, Italy
Birmingham, UK

Marcello Fera
Mario Caterino
Roberto Macchiaroli
Duc Truong Pham

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Special thanks go to the Organising Committee of the VII International Workshop on Autonomous Remanufacturing (IWAR), in particular, Dr. Marta Rinaldi, Dr. Pasquale Manco, Dr. Raffaele Abbate and Dr. Maria Antonietta Turino, who were the people that made the event come true.

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Finally, we thank Mr. Anthony Doyle, Ms. Amudha Vijayarangan and the Springer Team for their expert support in the commissioning and production of the book.

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Development of Sustainable Remanufacturing Systems: Literature Review



Paraskeva Wlazlak and Kerstin Johansen

Abstract Implementing remanufacturing as a strategy to achieve circularity in manufacturing companies offers significant benefits in terms of both environmental sustainability and financial performance. However, the development of sustainable remanufacturing systems is accompanied by various complexities and challenges. Companies engaged in remanufacturing must consider solutions that address the three dimensions of sustainability: economic, social, and environmental. Moreover, they need to tackle the unique characteristics associated with remanufacturing systems. This paper aims to investigate aspects covered in existing studies related to the development of sustainable remanufacturing systems. The methodology involves a literature review focusing on three aspects: (1) the triple bottom line of sustainability; (2) capabilities required for establishment of a sustainable remanufacturing system; (3) enablers that can support the development of a sustainable remanufacturing system. By classifying the published literature and conducting a thorough analysis, this paper provides valuable insights for practitioners and researchers, facilitating the creation and accumulation of knowledge in the field of sustainable remanufacturing systems. Furthermore, the paper aims to underscore the significance of this area of research and identify potential avenues for future investigation.

Keywords Remanufacturing · Sustainability · Circularity · Manufacturing system development

1 Introduction

The concept of sustainability has become paramount in urgency to reduce the impact on industrial activities on our planet [1, 2]. In strive to achieve a greener future, companies have started to redo their manufacturing processes to incorporate sustainable concerns [3, 4]. The attention towards sustainability performance has increased

P. Wlazlak (✉) · K. Johansen
School of Engineering, Jönköping University, Jönköping, Sweden
e-mail: paraskeva.wlazlak@ju.se

significantly, primarily because manufacturing can have adverse effects on the environment [5]. However, it is crucial to acknowledge that manufacturing also plays a vital role in promoting economic growth and societal well-being [6]. Because of the impacts on environment, society, and economic growth sustainable manufacturing has emerged as a concept [7]. Sustainable manufacturing has emerged as a concept that seeks to minimize environmental harm while maximizing the positive contributions of manufacturing to society. This is referred to as the triple bottom-line of sustainability [8, 9]. Thus, the performance of a manufacturing company should be holistically evaluated including not solely financial performance, but also social and environmental performance [1].

Among the new approaches remanufacturing systems have emerged as a solution that has the potential to foster a circular economy and is an important step towards achievement of sustainability development goals [1]. Remanufacturing is a process that involves restoring used products (or also called cores) to their original conditions and hence it has gained significant place in the research in the last decades [10, 11]. It offers benefits regarding minimizing of waste, resource consumption and mitigate the burden on landfills [12]. Remanufacturing systems enable companies to tap into the value of discarded goods, extend their life span hence contribute to economic and environmental sustainability aspects [13]. However, achievement of sustainable remanufacturing systems and its operation has its unique challenges and complexities [14] that are different from those that occur in traditional manufacturing such as low degree of automation and high manual work [15]. To ensure successful operations of a sustainable remanufacturing system that corresponds to internal and external requirements requires us to look into its development [1, 16]. Effective development of a system often is described with respect to 3 dimensions; process, people, and technology [17] which can be also applied to a remanufacturing system.

While the existing literature contains multiple literature reviews in the field of sustainable remanufacturing, with focus for instance on the role of emerging technologies in facilitating circular systems [18, 19] or performance indicators [13, 20] these reviews often lack a comprehensive or systems-oriented perspective when it comes to the development of sustainable remanufacturing systems. Such a holistic view is valuable for enhancing our understanding of the complex nature of remanufacturing systems. Furthermore, many of these reviews primarily concentrate on various circularity strategies, with remanufacturing being partially discussed [21, 22]. Consequently, there is a clear need for reviews that are specifically focused on remanufacturing as a key circular economy strategy.

Therefore, this paper delves into development of sustainable remanufacturing systems, exploring the different aspects that have been addressed in the existing research. Hence, the paper aims to answer the question ‘*What aspects have been addressed in the existing research on development of sustainable remanufacturing systems?*’.

By shedding lights into development of sustainable remanufacturing system, future research and direction can be proposed.

2 Introduction to the Main Topics

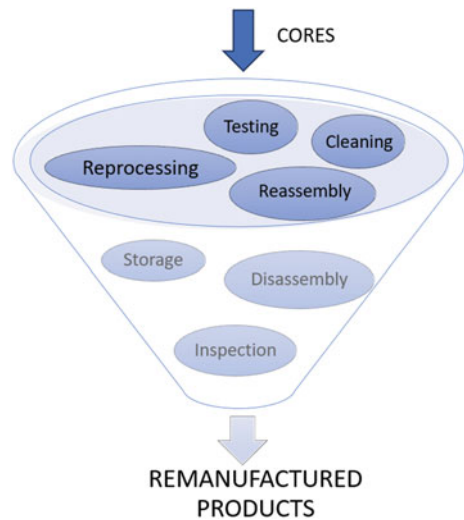
2.1 Remanufacturing System

Depending on the relation to the product manufacturer different companies can carry out remanufacturing activities. These are for example: (1) Original Equipment Manufacturers (OEMs) that remanufacture their own products; (2) contracted remanufacturers that carry out remanufacturing as a service to the OEMs; (3) and independent manufacturers that remanufacture products bought from other companies [1].

Remanufacturing encompasses the process of rebuilding used products (cores) to restore them to a useful state. The remanufacturing process involves several activities, including inspection, cleaning, disassembly, reprocessing, reassembly, storage, and testing, as depicted in Fig. 1 [10]. The order and purpose of these operations are not standardized and depend on individual remanufacturing cases and the specific requirements for core recovery [1].

Remanufacturing can be organized in multiple ways, presenting both similarities and unique characteristics when compared to traditional manufacturing. These unique characteristics introduce additional challenges that must be effectively managed within a remanufacturing system [15]. Some examples of these challenges include dealing with small batch sizes of mixed products and a low degree of automation, relying heavily on manual labor, comparable with high-mix low volume challenges [23]. Given the diverse nature of remanufacturing tasks, flexibility becomes a crucial requirement for a successful remanufacturing system [24]. To achieve profitability in remanufacturing, companies must address uncertainties

Fig. 1 Remanufacturing activities: adapted from Sundin and Bras [10]



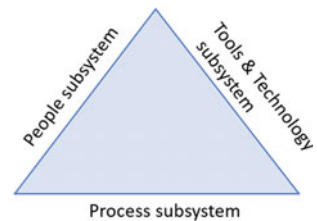
surrounding core quantities and qualities, process variations, and capacity requirements. Overcoming these challenges is essential, as failure to do so may result in an unprofitable remanufacturing endeavor [19].

2.2 Systems-Oriented Approach to Remanufacturing

A manufacturing system encompasses a series of manufacturing processes that enhance the value of inputs to generate desired outputs [1]. In this paper manufacturing and production are used interchangeably. The manufacturing process entails the utilization of machinery, tools, power, and labor. Adopting a systems perspective in manufacturing helps us approach it holistically and gain a deeper understanding of its complexity. A similar line of thinking can be employed when the focus is on remanufacturing. This systems-oriented approach focuses on the various components that constitute the system and their interrelationships. A system can be defined as a collection of interconnected components, such as people and machines, working together in an organized manner to achieve a specific goal [25]. Different researchers may have slightly different descriptions of the components of a (re)manufacturing system. For instance, Hubka and Eder [26] argue that the primary components of a transformation system are the transformation process, the operand, and the operator. The operators, which include the human system, technical system, information system, and management and goal system, drive the transformation process. The relationship among these components contributes to the conversion of input into output, involving a value-added transformation.

Morgan and Liker [17] propose a model for product development systems, which emphasizes the integration of three subsystems. Similarly, when examining remanufacturing development systems, we can observe the integration of process, people, and tools and technology subsystems (see Fig. 2). The process subsystem includes actions, activities/tasks, and decisions associated with remanufacturing development, the way the development is carried out. It focuses on waste removal and standardization to increase flexibility. The people subsystem covers individuals representing organizational functions and competences related to remanufacturing development. It involves coordinating efforts and developing technical skills across different disciplines. The tools and technology refers to the use of different tools, methods to support development of remanufacturing systems.

Fig. 2 A conceptual view of system approach to remanufacturing: adapted from Morgan and Liker [17]



The development of a (re)manufacturing system involves both its design and implementation. Previous research has highlighted that the practical development of manufacturing systems often lacks a systematic perspective, relying instead on ad hoc principles and uncertain, unstructured activities [25]. Manufacturing development is commonly described in terms of a project management stage-gate process. To address this challenge, literature and practical handbooks have proposed various processes and frameworks to support the development [25, 27].

3 Research Methodology

The aim of this paper is to investigate aspects covered in existing studies related to the development of sustainable remanufacturing systems. To achieve this, a literature review methodology was employed, following the recommendations of Jesson and Lacey [28]. The search was conducted in the Web of Science database using the search term “sustainable remanufacturing” within a period between 1999 and May 2023, resulting in 782 publications.

To refine the results and focus on relevant meso-level topics, four specific areas were selected: sustainability science, design and manufacturing, management, and manufacturing. Publications on other topics (for example, supply chain and logistics), were excluded, leaving a total of 249 identified publications. The literature overview encompassed various types of publications, including journal articles, conference papers, proceeding papers, and review articles. Two editorial materials were excluded as they were deemed irrelevant to the aim of the paper, resulting in a final selection of 247 papers.

The titles and abstracts of these papers were carefully reviewed for relevance, leading to the exclusion of many papers due to their lack of relevance to the subject area. Ultimately, 27 papers were considered relevant and progressed to the next step of the review process, which involved a thorough reading of the entire papers. To be included in the final review, these 27 papers needed to strongly focus on sustainability, remanufacturing systems, and development, excluding those that only briefly mentioned one of these areas. After conducting a thorough review of the papers, 15 additional papers were excluded from the study as they primarily focused on business models, the process of business model innovation, had a supply chain perspective, or only mentioned sustainability or remanufacturing systems. These papers were considered outside the scope of this study. The final selection of papers included 12, which were then classified based on their content. The classifications focused on three aspects: (1) the triple bottom line of sustainability; (2) capabilities required for establishment of a sustainable remanufacturing system; (3) enablers that can support the development of a sustainable remanufacturing system.

4 Literature Review Results: Sustainable Remanufacturing

This section is divided into two main sub-sections: “Descriptive overview” and “Aspects addressed”.

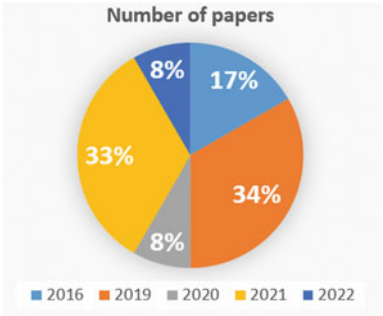
4.1 Descriptive Overview

Table 1 provided overview of the research methods employed and the topic addressed in the selected 12 papers. It revealed that 7 of the papers utilized literature review as their research method, while 5 papers utilized case studies.

Table 1 Overview of the selected papers

Ref	Method	Topic addressed
<i>Literature reviews</i>		
[13]	Literature review	Indicators for a circular economy
[18]	Literature review	The role of Fourth Industrial Revolution in remanufacturing in developing countries
[19]	Literature review	Smart remanufacturing and sustainable application of I4.0 enablers
[20]	Literature review	Decision support systems for sustainable (re)manufacturing
[21]	Systematic literature review	Information management for adopting CE strategies
[22]	Literature review	Considering the three sustainability dimensions for circular economy realisation
[29]	Literature review	Outline five research fields in remanufacturing literature and propose future directions
<i>Case study</i>		
[14]	Case study	Barriers (technical, economic, organizational, structural, legal and societal) and recommendations for achieving circular and efficient production systems
[15]	Case studies	Application of lean methods in industrial remanufacturing operations
[24]	Case study	Integrative perspective to drive sustainable value creation in remanufacturing contexts
[30]	Case study	Propose an environmental-impact based indicator that complements existing measures (mass-based indicators)
[31]	Case study	Interconnections between the lean and the circular systems

Fig. 3 Distribution of papers by year of publication



A total of 12 papers were included and they were categorized according to the year of publication (see Fig. 3).

4.2 Aspects Addressed

4.2.1 Sustainability Aspects

Table 2 presents a compilation of the selected papers along with the sustainability dimensions (economic, environmental, and social) they focus on.

Of the selected 12 papers, 11 focused on economic sustainability, addressing areas such as monitoring costs in remanufacturing operations and discussing productivity and profitability [14, 15, 19, 21, 22, 31]. Key performance indicators (KPIs) for

Table 2 Overview of sustainability dimensions

References	Sustainability dimensions		
	Economic	Environment	Social
Kristensen and Mosgaard [13]	x	x	
Despeisse et al. [14]	x	x	
Pawlik et al. [15]	x		
Chau et al. [18]		x	
Kerin and Pham [19]	x	x	x
Zarte et al. [20]	x	x	x
Acerbi et al. [21]	x	x	x
Lieder and Rashid [22]	x	x	x
Jensen et al. [24]	x	x	x
Esmailian et al. [29]	x	x	x
Haupt and Hellweg [30]		x	
Schmitt et al. [31]	x	x	

measuring economic sustainability were summarized, including net present value, life cycle costing, total cost of ownership, product reliability, cycle time, process flexibility, reuse rate [29]. The economic indicators in Zarte et al. [20] and Acerbi et al. [21] covered cost, profit, investments, quality, delivery, and flexibility. Regarding environmental sustainability, 11 of the papers emphasized the collection of environmental data, resource usage, emissions, and reducing waste and CO₂ emissions throughout the product lifecycle [14, 18, 21, 22, 31]. KPIs for measuring environmental sustainability included emissions, waste, energy consumption, and land use [29, 31]. Haupt and Hellweg [30] introduced the environmental-impact based REV indicator to measure retained environmental value through activities like reuse, remanufacturing, repairing, and recycling. Zarte et al. [20] discussed indicators related to material, energy, waste, and greenhouse gases. In terms of social sustainability, only six papers addressed this aspect, focusing on monitoring workers' ergonomic and safety conditions [21]. KPIs for measuring social sustainability encompassed equity, ethical considerations, employee welfare and development, employee turnover rate, training, employee health and safety, supplier commitment, and consumer satisfaction [29]. The social indicators in Zarte et al. [20] pertained to employee health and safety, satisfaction, and development.

4.2.2 Capabilities Required for a Sustainable Remanufacturing System

In Table 3, the identified capabilities necessary for establishing a sustainable remanufacturing system are presented. These capabilities are classified based on the three dimensions of a manufacturing development system: process, people, and tools and technology.

Remanufacturing systems possess distinct characteristics that distinguish them from traditional manufacturing [19, 29]. These unique features necessitate the development of specific capabilities. In particular, eight process-related capabilities were identified. The identified capabilities referred to system's capacity to effectively manage and adapt to uncertainties in volume and requirements. Additionally, capabilities focused on the system's ability to effectively manage situations where production volumes are low and process times exhibit high variability. It involved addressing the challenges associated with fluctuating demand levels, unpredictable processing times, and potentially inefficient resource allocation. Capabilities were also required to handle complexities related to production planning and control [15]. Many complexities were mentioned to arise from scheduling diverse workflows and remanufacturing activities based on the core's condition [15, 19]. Ensuring efficiency within remanufacturing systems presents a significant challenge [15]. In remanufacturing operations, ensuring that cores are reassembled with the exact same components can be challenging, especially when multiple cores are involved [15]. Furthermore, five people-related capabilities were highlighted. It was indicated that labor-intensive processes pose challenges [15], emphasizing the importance of providing a safe working environment. Upskilling operators with the necessary skills and competencies to effectively use digital technologies and handle highly variable tasks [14,

Table 3 Capabilities related to process, people, tools and technology

Capability	References
<i>Process</i>	
To adapt and adjust processes effectively in response to changing market dynamics and product demands	[15, 18, 19, 21, 29]
To adapt to variations, unpredictability, or fluctuations in the quality and quantity of inputs and outputs within the process	[15, 18, 19, 21, 29]
To handle low production volumes and highly variable process time	[15, 29]
To effectively handle inventory planning in response to market demands while addressing challenges related to inventory costs and waste	[29]
To effectively manage scheduling and coordination of various remanufacturing activities to ensure efficient and timely production	[15, 19, 21, 29]
To manage complexities caused by different product generations and the numerous variants often found within a product family	[15]
To effectively handle the disassembly of returned products into their component parts and subsequently reassemble them into functional products	[14, 15, 31]
To effectively oversee and coordinate operations that rely heavily on manual labor	[15, 29]
<i>People</i>	
To ensure a safe and ergonomic work environment that promotes the well-being, health, and safety of its workers	[21]
To identify, recruit, and develop personnel with the necessary skills and competencies to effectively operate and utilize digital technologies in the workplace	[18, 19]
To identify, recruit, and develop personnel with the necessary skills and competencies to handle highly variable and complex operations	[14]
To educate and inform personnel about the positive aspects and potential environmental consequences associated with industrial operations	[22]
To foster effective communication and collaboration between departments	[31]
<i>Tools and technology</i>	
To monitor and track the costs associated with remanufacturing processes	[21]
To monitor and track environmental impacts associated with remanufacturing processes (energy, material waste, and CO ₂)	[19]

18]. Two capabilities were related to tools and technology. They focused on the developing of the ability of the systems to monitor, gather and distribute information with respect to cost and environmental impacts [21, 31].

4.2.3 Enablers

In Table 4, the identified enablers necessary for establishing a sustainable remanufacturing system are presented. These enablers are classified based on the three dimensions of a manufacturing development system: process, people, and tools and technology.

Only one process-related enabler was revealed. It aids in decision-making regarding the implementation of remanufacturing practices and considers their economic and operational viability [31]. A single people-related enabler was recognized, focusing on training and education in various Industry 4.0 technologies, such as virtual reality (VR), augmented reality (AR), and human–robot collaboration. It emphasized the significance of sustainability and the benefits of utilizing IoT to drive progress and ensure quality. The training and education focused on providing knowledge on effectively managing multiple tasks, disassembly, and rework activities [15, 19, 22]. Eight tools/technology-related enablers were identified. Digital tools were particularly important for gathering information about product conditions [21]. The introduction of sensors in product design enables real-time data collection, facilitating the gathering of data and information on products throughout their life-cycle [22]. Utilizing supporting technologies like virtual reality (VR), digital tests, and digital line layouts provide a means to minimize the reliance on physical test assemblies. This approach effectively reduces material waste and CO₂ emissions associated with production preparation, leading to significant economic savings. Data generation and processing are of great importance in factory management,

Table 4 Enablers related to process, people, tools and technology

Enabler	References
<i>Process</i>	
Evaluation of economic and operative feasibility of a remanufacturing strategy	[31]
<i>People</i>	
Training and education	[15, 19, 22, 31]
<i>Tools and technology</i>	
Remanufacturing technologies with advanced automation levels	[18, 19, 21]
Decision support tools	[19, 21]
Simulations tools	[21]
Digital technologies of Industry 4.0 (IoT platform, Virtual Reality, Augmented Reality, and Big Data)	[14, 18, 19, 21, 31]
Design for X methods such as design for disassembly or remanufacturing	[14, 22, 29, 31]
ICT systems that enable product lifecycle management	[22]
Lean practices	[15]
IT infrastructure	[31]

allowing managers to have a comprehensive understanding of production situations and the success of remanufacturing operations. Automation devices, including robots, address workforce challenges in smart factories, where employees can focus on assembling complex parts while robots handle repetitive tasks, benefiting the social environment [18]. Additionally, Kerin and Pham (2020) explored the relationship between Industry 4.0 (I4.0) and Internet of Things (IoT) technology in terms of economic sustainability. They highlighted the potential for improved manufacturing efficiency and cost reduction through the adoption of these technologies. The authors also discussed the environmental benefits of implementing I4.0 and IoT in remanufacturing processes. However, they noted a lack of emphasis on the environmental impacts of I4.0 in the remanufacturing field. Additionally, the authors pointed out that the social sustainability effects of I4.0 in remanufacturing are similar to other areas where IoT is applied. These effects involved changes in the skills, attributes, and behaviors of the individuals involved. To reduce variability, best practices for disassembly should be documented and shared with employees to make such operations more effective. Furthermore, Pawlik et al. [15] discussed the application of lean methods (e.g. standardization, visual management, 5S, Total Productive Maintenance) in industrial remanufacturing operations.

5 Discussion and Conclusions

The aim of this review paper was to examine the various aspects addressed in existing studies concerning the development of sustainable remanufacturing systems. The study primarily focuses on sustainability at a micro level, which pertains to the organizational level [11]. The identified indicators are designed to evaluate the sustainability of companies' remanufacturing systems, while some indicators also assess the contribution of remanufacturing towards achieving broader sustainability goals. Kristensen and Mosgaard [13] emphasize that the primary focus in remanufacturing activities lies in ensuring economic viability and environmental sustainability. This review highlights that the majority of emphasis is placed on the economic and environmental dimensions of sustainability, while the social dimension receives comparatively less attention. However, six of the reviewed papers highlighted the importance of balancing between environmental impacts, costs, and social impacts when making decisions related to sustainability in a remanufacturing system [22, 24, 29]. It is underscored the importance of establishing sustainability performance objectives and indicators to measure the effectiveness of a remanufacturing system across economic, environmental, and social dimensions. However, despite the growing body of research, there is a lack of tools, methods or frameworks that could support the development of remanufacturing systems capable of effectively balancing all three pillars of sustainability. The lack of frameworks integrating sustainability principles into the development of manufacturing systems is underlined by prior research [3, 4].

To achieve optimal performance in terms of these sustainability dimensions, it is crucial to design and develop remanufacturing systems with the capability to meet

these performance requirements. The design and development process of a manufacturing system plays a critical role in achieving the desired sustainable performance [16]. Johansson et al. [1] underscore the importance of implementing appropriate development processes that align with sustainability objectives at every phase of the development. Overall, the reviewed literature provides insights into important sustainable objectives and indicators, but falls short in providing evidence on how to develop remanufacturing systems that effectively meet these objectives.

This study indicated unique capabilities that are required for a remanufacturing system, and they are related to process, people, tools and technology. Remanufacturing systems require specific capabilities to effectively manage and adapt to uncertainties in volume and requirements, handle complexities related to production planning and control, and address challenges associated with labor-intensive processes [21, 29]. In addition, this study investigated the enablers that can facilitate the establishment of sustainable remanufacturing systems. Among the dimensions of process and people, only one specific enabler was mentioned, while the primary emphasis was placed on the role of tools and technology as enablers for achieving sustainable remanufacturing systems. However, the link between these enablers and the sustainable performance of the system remains unclear. There seems to be a common assumption that introducing certain enablers into a remanufacturing system will automatically improve its sustainability performance. This review highlights a deficiency in establishing explicit connections between the identified enablers for sustainable remanufacturing systems and the corresponding performance objectives and indicators. Consequently, the effects of these enablers on fulfilling different performance objectives during the operational stages of the systems' life cycle remain unclear. There are some exceptions, for example the literature review by Kerin and Pham [19] provide a discussion regarding the impact of existing and emerging digital technologies on the three pillar of sustainability.

In conclusion, further research is needed in several areas. Firstly, there is a need to develop guidelines, processes, and frameworks that specifically support the development of sustainable remanufacturing systems. Designing and developing for sustainability in the context of remanufacturing systems requires additional research and investigation.

Moreover, there is a pressing need for a well-defined development process that takes into account the sustainability pillars at each phase of the remanufacturing system development. A sustainability performance-driven approach is essential, with the goal of integrating sustainability considerations at every stage of the remanufacturing system development process.

A holistic perspective is essential during the development of sustainable remanufacturing systems, considering the dimensions of people, process, tools and technology. A more holistic perspective is necessary to effectively develop and understand the complexities of sustainable remanufacturing systems development.

A future study could expand its scope by concentrating on databases such as SCOPUS.

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Artificial Intelligence in Remanufacturing Contexts: Current Status and Future Opportunities



Valentina De Simone , Gerardo Luisi , Roberto Macchiaroli ,
Fabio Fruggiero , and Salvatore Miranda

Abstract Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), rapidly evolving in both academia and practice, allow for improved manufacturing processes thanks to data analysis. These technologies provide benefits to production systems in several ways by enabling resilience and improving sustainable growth. However, the manufacturing challenges and issues need to be revised according to the new trends provided by remanufacturing, i.e., an emerging and new “mode” of manufacturing able to bring used products to a “like-new” state, potentially profitable and less environmentally harmful compared to the classical manufacturing systems. This research work, methodologically based on a scoping literature review, provides the state-of-the-art related to AI, ML, and DL use in remanufacturing contexts, identifying the main field of applications and their challenges and limitations. The findings revealed an increasing interest in the topic in the last three years. Most of the studies focused on disassembly and inspection processes, whereas further applications (e.g., repair, demand forecasting, cost prediction, etc.) have not been fully investigated and need further research. DL represents the most widely used technique (followed by ML). Even though the literature confirmed that AI-based methods could increase productivity and lower time and costs, further attention needs to be paid to real industrial case study applications.

Keywords Sustainable development · Circular economy · Remanufacturing

V. De Simone (✉) · S. Miranda

Department of Industrial Engineering, University of Salerno, 84084 Fisciano, SA, Italy
e-mail: vadesimone@unisa.it

G. Luisi

Parthenope University of Naples, Naples, Italy

R. Macchiaroli

Department of Engineering, University of Campania Luigi Vanvitelli, Aversa, Italy

F. Fruggiero

School of Engineering, University of Basilicata, Potenza, Italy

1 Introduction

Remanufacturing is one of the key elements of the circular economy, i.e., a production and consumption paradigm that aims to maintain the circulation of products, components, materials, and energy for adding, restoring, and maintaining their value over a long time [1]. Keeping resources in use for as long as possible allows for less extraction of new raw materials and reduces waste, leading to more sustainable economic growth. In this picture, remanufacturing aims, in particular, to “return a used product to at least its original state with a warranty that is equivalent to or better than that of a newly manufactured product” [2, 3]. The concept of remanufacturing is not new at all. Already in 1985, Lund, a Boston University professor, introduced this typology of industrial process in which a new product can be reassembled from an old one and, where necessary, new parts are used to produce fully equivalent, and sometimes superior in performance and expected lifetime, to the original new product [4]. Remanufacturing plays a significant role in solving the problems of environmental pollution and resource shortage, as well as promoting global economic and social development since the basic raw materials are represented by second-hand products or cores collected from consumers so that the residual valued-added in forms of materials, energy, and labour can be captured and re-used [5].

The remanufacturing process generally starts with acquiring used products, which are then inspected to determine the quality conditions. After and according to the quality condition, used products are disassembled into corresponding constituent components, which are then reprocessed. Once all constituent components are reprocessed, these are reassembled and tested before being sold as remanufactured products [6, 7]. This process hides several problems, such as uncertainty regarding the quality conditions, quantity, and timeframe for the return of materials and components to be remanufactured, refurbished, or reused; the balance of customer demand with used-products supply, and the way to produce, plan, and generate demand for manufactured and remanufactured products simultaneously [1, 8–10].

The digital transformation enabled by the Industry 4.0 paradigm can help in overcoming some of these problems or at least reduce their impacts on the system. In particular, the increasing digitalization and the integration of smart devices and machines in production systems are more and more able to provide large amounts of data that can be stored, processed, and analysed. In this context, it is worth mentioning the growing interest in applications of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) methods in the manufacturing environment. AI, a broad field of computer science, allows to building of smart machines capable of performing tasks that typically require human intelligence [11]. ML and DL instead represent the two essential sub-fields of AI. ML allows computers to recognize data correlations and make human-like decisions without defining rules. It is based on a generalization of data knowledge and can be realized by different methods, such as classification, clustering, regression, and anomalous detection [12]. DL, instead, refers to data-driven learning approaches that use multi-layer neural networks and processing to compute. The term “deep” highlights the high number of levels or stages through which data is processed to develop a model [11].

AI, ML, and DL are increasingly being used to extract from data knowledgeable value, which can bring many benefits. In manufacturing, AI-based tools and services can support decision-making processes by reducing the dependence on employee experience, improving time-consuming activities typically performed by workers, and/or outperforming the classical analytical approaches to problems. Typical applications range from demand-side management to condition monitoring, predictive maintenance, quality, production planning, production control, and supply chain management [12–14]. The implementation of technology can enable time and cost savings, increase quality and waste reduction, and facilitate manufacturing development in smart, flexible, and eco-friendly production ecosystems [15].

Even if it seems clear that AI, ML, and DL can support and improve manufacturing processes [13, 16], these techniques are less investigated in remanufacturing contexts. The classical manufacturing challenges solved by AI, ML, and DL approaches need to be adapted, revised, and integrated into the remanufacturing context. Until now, researchers have focused on the use of these technologies in the overall paradigm of the circular economy [17] or more in general on the enabling technologies provided by Industry 4.0 in the remanufacturing context [18]. However, to the best of the authors' knowledge, the scientific literature lacks a comprehensive overview of the use of AI, ML, and DL in the remanufacturing context, and this represents the main gap that this research study wants to address.

For this reason, the main aim of this research study, methodologically based on a scoping literature review, is to provide an overview of state of the art related to the use of AI, ML, and DL in remanufacturing contexts identifying the main field of applications and their challenges and limitations.

The remainder of the paper is structured as follows. Section 2 outlines the research methodology used. In Sects. 3 and 4, respectively, the key outcomes of the quantitative and qualitative analysis of the literature are presented. Lastly, Sect. 5 summarizes the main conclusions of the carried-out research study and reports the future research directions.

2 Methodology

To fill the gap already defined, the existing scientific literature was examined using a scoping review, that summarizes complex and heterogeneous topics, to identify research gaps and set the scene for a future research agenda [19], has been carried out to examine the scientific literature and address the following two Research Questions:

- RQ1: What are the main application areas of AI in remanufacturing?
- RQ2: What are the main methods used, limitations, and advantages?

After the identification of the RQs, it has been possible to define all the research keywords needed for the search of the relevant articles. A combination of keywords was used to investigate the research topics related to remanufacturing with those

related to artificial intelligence techniques. The keywords “remanufact*” and “re-manufact*” (Group A) were searched in combination with all of the following words “Machine Learning”, “Deep Learning” and “Artificial Intelligence” (Group B). The asterisk character was used to include in the search all words that have in the root “re-manufact” and “remanufact”. The search, concerning titles, abstracts, and keywords of the articles, was carried out using the Scopus database and limited only to conference proceedings, articles, and reviews, published from 2013 onwards, without distinction of thematic areas. The relevant articles were selected through two steps of analysis. The first step involved reading the title and the abstract of the articles. In this phase, the rejected articles were excluded because the research topic was not related to remanufacturing and AI technologies, no full text was available or duplicated articles. The second step involved the reading of the full text of the papers selected and the identification of the most relevant articles based on the same exclusion criteria described above.

After the selection of the relevant research studies, the carried-out analysis was focused on:

- **Quantitative analysis:** main characteristics of papers such as authors, year of publication, type of document, and innovative contribution.
- **Qualitative analysis:** the industrial sector (e.g., electronics, automotive, etc.), the type of task investigated/improved by AI applications (e.g., inspection, disassembly, repair, etc.), the different AI methods, and the advantages and disadvantages or limitations revealed.

3 Quantitative Results

From the initial search, carried out in April 2023, 121 articles were obtained. After the first screening phase, 50 articles were selected, whereas after the second phase of the selection process, only 18 articles out of 121 were defined as relevant. For the selected articles, the year of publication was analysed. From Fig. 1, it is possible to notice a trend in the number of articles published, which sees growth in 2021 compared to previous years, after which the trend remains constant. Most of the articles (14 out of 18) have been published in the 2021–2023 range, testifying to the increased interest in the application of AI in remanufacturing, also due to the important advantages it brings to sustainability goals. As regards the type of articles, the selected documents are not divided equally, but there is a greater presence of articles (10 articles-[20–29]) than conferences (7 articles-[30–36]) and reviews [37].

Considering the authors’ country, the selected articles show greater attention towards re-manufacturing by China (6 articles), the United Kingdom (5 articles) and Germany (4 articles). Some of these countries are promoting a relevant push given by national governments, which have promulgated a series of laws and regulations regarding remanufacturing to help and support the development of remanufacturing industries. The articles have been also classified according to the type of innovative

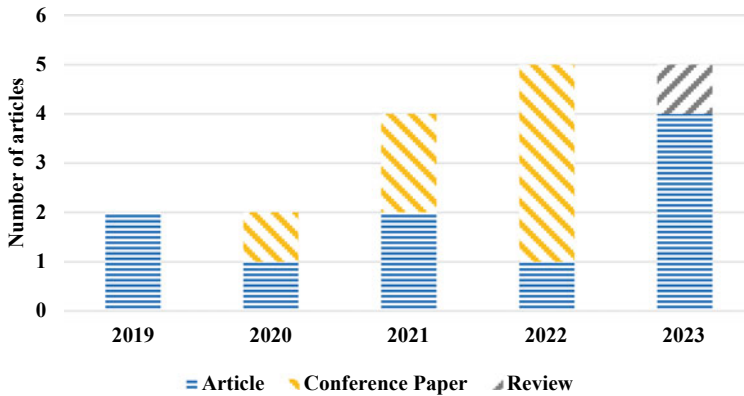


Fig. 1 Time distribution and type of document of selected publications

contribution distinguishing between articles that provided an overview or state-of-the-art analysis of the application of AI in remanufacturing and articles that dealt with the development and the implementation of models for specific applications in this field. Among the selected articles, 15 dealt with the development and implementation of a model, and instead, 3 focused on an overview of AI applications in remanufacturing, respectively focusing on inspection [31], disassembly [30], and repair process based on Additive Manufacturing (AM) [37]. The following section provides further details on the results of the analysis conducted and focused on the articles related to the development and implementation of an AI-based model in remanufacturing contexts.

4 Qualitative Results

4.1 Application Areas of AI in Remanufacturing

First of all, for each article that proposed a method, the area of application has been identified. From the analysis emerged great interest for the disassembly phase (6 articles) followed by inspection (5 articles). These two kinds of processes are the most complicated in the remanufacturing process. Regarding the disassembly, it aims to retrieve parts from the returned products. Due to the dimensional uncertainties and geometrical variations in the returned products, disassembly is also usually carried out manually. To face the limitations of a highly human-dependent process, much interest has been focused on using robotics and generating the best disassembly sequence [21, 22]. Also, the inspection process is generally performed by an operator. To overcome problems related to high time, labour cost, and individual subjectivity,

automated inspection techniques have been developed to help or replace human decisions by using intelligent and smart approaches based on AI, ML, and DL [20, 23]. Less investigated the applications in the field of repair components for remanufacturing and decision-making processes such as the prediction of remanufacturing time and cost or demand forecasting of remanufactured products.

In addition, an analysis of the sectors for which the models have been developed has been conducted. Most of the articles (6 articles) provided applications for general machining followed by electronic components (4 articles). The models developed by researchers have been also implemented. It is interesting to highlight that only 6 out of 15 were based on real case studies in industrial contexts. The others have been conducted in the laboratory. It is highlighted by researchers the need for validation and application in real contexts given the much complex situation that could arise compared to the laboratory environments. The details related to the analysis of the articles, including the AI, ML, or DL methods used, are reported in Table 1.

4.2 AI Methods in Remanufacturing, Advantages and Limitations

Regarding the methods used, the findings revealed a greater use of DL-based models. The reason that leads to the greater use of the DL can be found in the type of AI application classes treated in the research works analysed. There is a majority of computer vision applications that are based on the analysis of unstructured data such as images and videos. In the field of ML, 2 papers focused on reinforcement learning [21, 24], only one study on Support Vector Regressor (SVR) and semi-supervised learning [28], and one on tree-based ML models [27].

In general, each article focused on the application of a single model, only in 2 cases the combination of two models is exploited [26, 35]. Furthermore, in 6 articles [22, 26–28, 35, 36] a comparison between the models developed and other models applied in previous studies or usually used for similar applications in manufacturing is also addressed.

Disassembly

The disassembly has the purpose of recovering the parts of the products to be regenerated to be able to carry out regeneration evaluations on each component. Due to the variability of the types, dimensional uncertainties, and geometric variations in the products to be regenerated, disassembly is usually performed manually, or in any case, it is a highly manual phase and labour-intensive [30]. As the remanufacturing process grows in scale, however, it is necessary to increase the efficiency of disassembly through its appropriate automation.

One study [24] presents a hybrid disassembly system, not fully automated, composed of manual, autonomous, and rigidly automated workstations. The system is designed to combine the advantages of the two types of disassembly, manual and

Table 1 Articles' analysis details

Refs.	Area of application	Laboratory/Industry	Sector	AI, ML, or DL method
[20]	Inspection	Laboratory	Machining	Deep Learning (DL)-based Computer Vision
[21]	Disassembly	Laboratory	Electronics	Reinforcement Learning
[22]	Disassembly	Laboratory	Machining	Deep Reinforcement Learning (DRL) based on deep Q-network (DQN)
[23]	Repair	Industry	Machining	Faster R-CNN
[35]	Disassembly	Laboratory	Electronics	Convolutional long short-term memory (ConvLSTM) and You Only Look Once (YOLO)
[24]	Disassembly	Laboratory	/	Deep Reinforcement Learning (DRL) based on Deep Q-network (DQN)
[36]	Disassembly	Industry	Electronics	YOLOv5
[25]	Inspection	Laboratory	Automotive	Deep CNN (DCNN)
[33]	Inspection	Laboratory	Automotive	CNN
[26]	Inspection	Industry	Automotive	DeepLabV3+ and YOLOv5
[32]	Disassembly	Laboratory	Machining	Faster R-CNN
[34]	Inspection	Laboratory	Machining	Deep CNN (DCNN)
[27]	Demand prediction	Industry	Electronics	Linear regression, single tree-based ML models (i.e., CART and M5), Random Forest (RF), and Artificial Neural Network (ANN)
[28]	Cost prediction	Industry	Machining	Semi-supervised Least Squares Support Vector Regression (SLS-SVR)
[29]	Remanufacturing timing prediction	Industry	Steel	Deep Belief Network (DBN)

automated, to manage the variance and uncertainty of the product to be disassembled; furthermore, through an algorithm based on Deep Q-Network (DQN), the flow of materials is managed, the algorithm manages to successfully assign the individual products to the appropriate stations, based on the respective conditions in which it is located. In this way, when a product, due to the high uncertainty, cannot be disassembled by an autonomous station, the DQN system sends it to a manual station,

where the success of the disassembly operation is ensured, at the cost of higher time. A method of automatic generation of the disassembly sequence exploiting the visual recognition based on Faster R-CNN [32] is proposed, which is applied to case studies of different scenarios on the coupling of the dual-axis diaphragm. In [22], instead, a disassembly information model considering parts failure features based on the fuzzy evaluation method is defined. Instead, in the study proposed by Serrano-Muñoz, the use of two state-of-the-art RL algorithms has been investigated to learn the object extraction skill when applied to the contact-rich disassembly task [21]. The study provided by Mangold et al. [36] presented a model for classifying the screw head using YOLO architecture, an object detector in the field of deep learning applications, to configure the right tool for the disassembly task performed by the robot and adapt its movement. Lastly, an interesting study [35], in the field of human motion prediction in disassembly, investigated the use of Convolutional Long Short-Term Memory (ConvLSTM) to predict the next frame image and YOLO architecture to identify the human hand object. When disassembly includes the simultaneous actions of humans and robots, human motion prediction is essential to avoid any collision and prevent damage.

The main advantages reported in the analysed papers are related to the reduction of disassembly times through the elaboration of the optimal disassembly sequence and the use, in collaboration with man or not, of automatic robotic disassembly systems [22, 24, 32], cost reduction [24] and higher efficiency of disassembly process if compared to traditional existing approaches [32].

The main limitations instead are related to the simplification of the problem [22, 24, 32] and the need for larger datasets [24, 36].

Inspection

Among the articles analysed, 5 deal with the problem of the automation of the inspection/classification phase. Approaches based on Convolutional Neural Networks (CNN), deep learning architectures inspired by the natural mechanism of visual perception of living creatures and successfully applied in image recognition, are used to improve the decision-making aspect of wear zone assessment, reducing the workload, and consequently increasing productivity [20, 25, 26, 33, 34]. These approaches are based on computer vision, an interdisciplinary field extremely useful to inspection applications. One study [26] deals with the wear classification of mechanical bearings through the combination of two models: YOLOv5 and DEEPLABv3, obtaining as a result a greater accuracy of the classification.

The applications of AI, ML, and DL make possible to improve the accuracy of manual inspection making the process more reliable eliminating the pure dependence on operator judgment, and reducing errors [25, 26, 33]. These approaches enhance speed in the process [25, 33] and reduce the number of accidents [25]. Better decision-making processes are guaranteed by remanufacturability evaluation [20] and, in general, the solutions proposed are simple and economically convenient [34].

Regarding the limitations, instead, the studies revealed that the application of models in terms of products analysed is complex to generalize [20, 23] and in some cases, it is difficult to allow scalability to an industrial context [25, 34].

Further Applications

Only one study, in the field of the repair process in remanufacturing, proposed a deep learning model to detect the damaged region of fixed bends and define accurately the geometry of the damaged area for a robotic laser cladding repair cell [23]. This approach allows for a reduction of time and cost related to inspection of the product maintaining the accuracy and precision of the repair process. However, this approach is not generalizable and has been proven to be effective only in repairing cylindrical parts.

Regarding further applications investigated in the literature, the study conducted by Zhang et al. [28] proposed a model based on support vector regression and semi-supervised learning for predicting remanufacturing costs. The model can help remanufacturing enterprises by providing remanufacturing costs according to the failure characteristics of the components so that the remanufacturability is easier to evaluate. However, the study revealed the difficulty in obtaining experimental data and general limitations caused by the lack of data.

For the evaluation of the optimal remanufacturing timing [29], a model based on deep belief networks (DBN) has been developed. The model bases its evaluation on several kinds of inputs (such as the planning cost, the disposal service cost, the remaining value, the annual cost increase, the parts regeneration ratio, etc.). A real case study related to a steel company that wants to examine the regeneration of the rolling mill gearbox has been provided. Decision-makers can make the right decision according to the results obtained maximizing the economic benefit and improving the quality performance. Both applications help in making decisions in the remanufacturing contexts quickly.

Lastly, the study carried out by Nguyen et al. [27] instead focused on demand prediction for the remanufactured products, which is fundamental for the marketing strategy needed for the remanufacturing sector, to provide a comprehensible prediction model and clearly define the effects of market factors on customer demand. Using structured and unstructured data from Amazon, the study revealed that Random Forest outperformed in terms of predictive performance the other models applied (linear regression, CART, M5, and Artificial Neural Network).

To conclude, the main findings obtained have been reported in Fig. 2. According to the macro phases of remanufacturing processes provided by Caterino et al. [7], the framework highlights in which phases/processes AI, ML, and DL are mainly implemented and reports the main advantages and limitations revealed by the carried-out literature analysis.

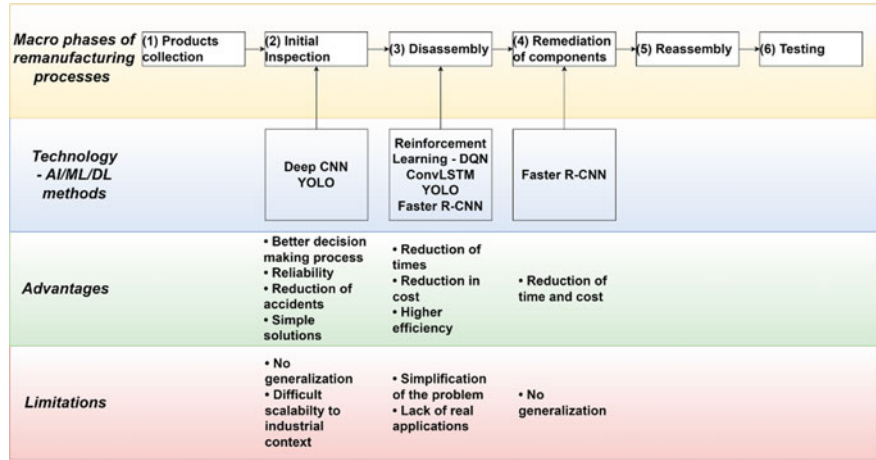


Fig. 2 AI, ML, and DL in the remanufacturing process

5 Conclusions

In conclusion, this research work, methodologically based on a scoping literature review, presents an overview of the use of AI, ML, and DL in remanufacturing contexts aimed at identifying the main application areas in these kinds of contexts and the main AI-based methods for each of them providing information also on limitations and advantages. The findings revealed an increasing interest in the topic above all in the last three years. Regarding the area of application, most of the studies selected for the review focused on disassembly and inspection whereas further applications related to other macro-phases of remanufacturing process or decision-making and planning processes (e.g., demand prediction, etc.) have been not fully investigated until now. The analysis showed that DL is the most widely used technique. For example, in inspection processes, strong use of computer vision has favoured the implementation of algorithms based on DL, suitable for working with unstructured data such as pictures and videos.

However, even if lots of advantages can be obtained by using these smart technologies (reduction of time, reduction of cost, etc.), the carried-out analysis also revealed that some problems and limitations are still present in this field. Models in some cases worked on small amounts of data, so possible performance improvements need to be evaluated in case of a more significant dataset. In addition, the variety of products against which the models have been tested is low, and in most cases it is reduced to a single type of product, not even considering its variants and this means to practically lower the level of complexity and variability that characterize remanufacturing processes.

In terms of future research directions, to obtain a more accurate picture, the individual types of applications for which AI, ML, and DL have not been thoroughly investigated should be explored (e.g., demand prediction, cost prediction, etc.). Inspection and disassembly look at the remanufacturing process from, strictly speaking, a productive point of view, other applications instead refer more to the planning or in general decision-making upstream and downstream processes in remanufacturing.

It should also be useful to provide single-sector analyses, starting from the most investigated at the moment. Moreover, since only tests in real environments guarantee the effectiveness of the models for specific use cases and scenarios, a focus on case studies developed with real industrial enterprises should be useful to investigate the lack and challenges from a real point of view. Research should help in the real application of these technologies by providing frameworks or decision support systems for remanufacturing applications in the real world.

Another interesting aspect to further investigate is linked to the economic feasibility of these solutions. The application of AI, ML, and DL is generally motivated by the reduction of errors and time of manual labour to lower the overall cost. However, no reference to models that evaluate the economic feasibility, which considers the overall cost for the development of the solutions and their implementation over the effect on the manufacturing systems, are provided in the literature.

Nevertheless, this study has some limitations e.g., the search strategy could be enhanced by using multiple scientific databases. Additionally, a backward search to identify relevant work cited by the articles and/or a forward search to find all articles that have cited the articles reviewed could have been performed. Moreover, considering the presence of keywords only in the article title, abstract and keywords could have affected the set of eligible articles. For example, the use of AI, ML, and DL in combination with other technologies (such as Augmented or Virtual Reality), even if investigated in the literature, could have been not included in this preliminary overview.

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Robotic Disassembly Sequence Planning and Line Balancing—Research Trends Review and Bibliometric Analysis



Natalia Hartono  and D. T. Pham 

Abstract Remanufacturing offers benefits to the environment, society, and the economy. Disassembly is the first and most critical operation in remanufacturing. With advancing technology and increasing labour costs, there has been an interest in automating disassembly. Robotic disassembly sequence planning and line balancing are two extensively studied topics in this area. This article establishes a connection between robotic disassembly sequence planning and line balancing and identifies trends through an extensive literature review and bibliometric analysis, shedding light on the research landscape. The findings reveal significant gaps in the literature. While artificial intelligence and machine learning are used in robotic disassembly sequence planning, their integration into robotic disassembly line balancing remains unexplored. Robotic disassembly sequence planning predominantly uses a single-objective approach, while robotic disassembly line balancing adopts a multiobjective nondominated approach, with the genetic algorithm, evolutionary algorithm, and bees algorithm as the most commonly used metaheuristics. These results offer insights and directions for further research in this domain.

Keywords Robotic · Disassembly · Sequence planning · Line balancing · Remanufacturing

1 Introduction

Remanufacturing is recognised as a pivotal component of a circular economy (CE) due to its numerous benefits [1]. It not only allows products to be restored to a condition equal to or better than new [2, 3], benefitting both remanufacturers and consumers, but also generates higher profits compared to other recovery options [4, 5]. Moreover, remanufacturing plays a vital role in promoting environmental sustainability by significantly reducing landfill waste, energy consumption, raw material usage, and greenhouse gas emissions [5–7]. Keeping end-of-life (EoL)

N. Hartono (✉) · D. T. Pham
University of Birmingham, Birmingham B15 2 TT, UK
e-mail: nxh886@alumni.bham.ac.uk

products in circulation for longer further enhances the environmental sustainability aspect of remanufacturing.

Disassembly is the first step in the remanufacturing process [8–13]. Effective disassembly enables remanufacturers to obtain high-quality components and materials that can be further processed and utilised in the production of remanufactured products. Robotic systems can improve the economic viability of disassembly operations [14]. Research into the optimisation of robotic disassembly encompasses various key areas, with a notable emphasis on sequence planning and line balancing [15–17]. Sequence planning involves determining the optimal order of disassembly [8, 9, 18], while line balancing ensures an even distribution of workload among robots [15, 16, 19]. By addressing these factors, the efficiency of robotic disassembly in remanufacturing can be maximised.

The relationship between sequence planning and line balancing has been acknowledged [15–17], yet previous research has not explored the existing literature on the link between robotic disassembly sequence planning and line balancing. The research reported in this paper aims to fill this gap by conducting an extensive literature review and bibliometric analysis on robotic disassembly sequence planning (RDSP) and robotic disassembly line balancing (RDLB) to identify trends in and interconnections between the two areas of research. The paper concludes with a summary of the key findings and future research directions.

2 Robotic Disassembly

The use of robots to perform disassembly has the potential to increase the amount of strategically important materials that can be recovered from EoL products [20] and improve industrial processes [21]. Researchers have investigated automated methods for disassembly; however, it is still understudied [22]. The process of robotic disassembly poses unique challenges in comparison to manual disassembly, primarily due to the distinct kinematic and dynamic characteristics of robots and humans [8, 17, 23, 24]. In particular, collision avoidance is a critical factor to consider when devising a plan for robotic disassembly [8, 17], which increases the overall disassembly time [8, 16]. More research is needed to optimise robotic disassembly and make it economically viable for widespread adoption.

RDSP and RDLB are recognised as NP-complete and intractable problems that are not suitable for treatment by mathematical programming methods when the size of the problem is large [25–27]. Previous research has predominantly used metaheuristics for their ability efficiently to find near-optimal solutions to complex problems in a reasonable amount of time [8, 18, 28–30].

This research solely focuses on robotic disassembly without human involvement, excluding studies related to human–robot collaboration due to inherent differences in capabilities and dynamics. A search through May 2023 in the Scopus database using the keywords “robot*” AND “disassembly” AND “sequenc*” yielded 42 articles on RDSP. Full articles written in English were verified. As indicated in Table 1

(see the detail in the Appendix Tables A.1 and A.2), the majority of the research is focused on minimising time, and only a few address sustainability (highlighted in bold) [4, 14, 31–33]. Previous studies on RDSP mainly used metaheuristics such as the genetic algorithm (GA), evolutionary algorithm, and bees algorithm (BA) in either single-objective (SO) or multiobjective (MO) aggregate approaches, with limited use of MO nondominated (MO-ND) approaches. However, conflicting objectives necessitate adopting a nondominated approach to consider multiple objectives without compromising feasibility [28]. Performance measurement remains limited, but the statistical performance metric (SPM) introduced by [14] explores the use of statistical methodology for performance metrics and optimal parameter settings, making it of interest for future use.

As previously mentioned, efficient robotic disassembly relies on two fundamental concepts: RDSP and RDLB [15, 16, 34]. Previous research has mainly focused on presenting a feasible disassembly sequence to achieve line balancing [15, 16]. Recent studies in manual disassembly have underscored the importance of sequence-dependent disassembly line balancing [35–41], which has also been extended to the field of robotic disassembly [15, 19, 34, 42]. Notably, sequence-dependent disassembly line balancing challenges the conventional viewpoint by simultaneously improving both the sequence and the line [15, 16]. An optimised and feasible disassembly sequence significantly enhances the efficiency of line balancing by enabling the optimal allocation of tasks. The search using the Scopus database identified 70 relevant articles on robot disassembly line balancing and sequence planning using the keywords “robot*” AND “disassembly” AND “line” AND “balancing” OR “sequenc*”. After screening for non-English language and survey papers, 37 articles were selected. While the formal description of DLB can be traced back to 2002 [18, 43], research on RDLB began in 2011 and has gained momentum since 2019. Table 1 presents the literature on RDLB, showing a greater focus on sustainability objectives compared to RDSP, with 18 articles dedicated to this aspect. Notably, two articles [44, 45] initially identified their work as RDSP, but upon closer examination, their methods and results align more closely with the field of RDLB. Hence, these articles have been reclassified as RDLB in the table. The prevalent adoption of the MO-ND and metaheuristic approaches for solving RDLB is evident in the literature. Performance measurement is more commonly used in RDLB compared to RDSP. In addition, the table reveals significant gaps for future research, including limited exploration of artificial intelligence (AI) and deep learning applications and other types of line balancing, such as U-lines and parallel lines. Due to space constraints, the full details of Table 1 are available in Tables A.1 and A.2. in the Appendix which gives the objectives, approach, and output of the research.

Table 1 RDSP and RDLB literature review in a concise form

RDSP		RDLB	
Author(s)	Method	Author(s)	Method
Suzuki et al. [46]		Radaschin et al. [43]	
Sundaram et al. [47]		Minca et al. [48]	
Baeza et al. [49]		Minca et al. [50]	
Puente et al. [51]		Filipescu et al. [52]	
Uhlmann et al. [53]		Liu et al. [19]	**, MO-ND, V
Kim et al. [54]		Gao et al. [42]	**, MO-ND
Gil et al. [55]		Alshibli et al. [25]	**, MO
Elsayed et al. [56]	**	Octavian et al. [57]	
Elsayed et al. [27]	**, SO	Fang et al. [58]	**, MO-ND, V
Vongbunyong et al. [59]		Fang et al. [60]	**, MO-ND, V
Popescu et al. [61]		Ming et al. [62]	SO
Alshibli et al. [63]	**, MO, V	Liu et al. [64]	**, MO-ND, V
Friedrich et al. [65]		Cil et al. [66]	**, SO, V
Vongbunyong et al. [67]		Fang and Xu [68]	**, MO-ND, V
Friedrich et al. [69]	SO, V	Fang et al. [70]	**, MO-ND, V
Parsa and Saadat [71]	**, SO	Liu et al. [15]	**, MO, V
Wang et al. [72]		Fang et al. [73]	**, MO-ND, V
Laursen et al. [74]		Fang and Xu [75]	**, MO-ND, V
Liu et al. [8]	**, SO, V	Chen et al. [34]	**, MO-ND, V
Costa et al. [76]	SO	Dong et al. [77]	**, MO-ND, V
Alshibli et al. [32]	**, SO	Zhang et al. [78]	**, MO-ND, V
DiFillippo and Jouaneh [79]		Lei et al. [80]	**, MO-ND, V
Laili et al. [23]	**, SO, V	Wang et al. [44]	**, MO-ND, V
Zhang et al. [81]	**, SO, V	Mei and Fang [82]	MO-ND, V
Lan et al. [83]		Tseng et al. [84]	**, SO, V
Ramírez et al. [85]	**, SO, V	Zeng et al. [45]	**, MO-ND, V
Chen et al. [17]	**, SO, V	Zhou and Bian [86]	**, MO-ND, V
Watanabe and Inada [87]		Yin et al. [88]	**, MO-ND, V
Wang et al. [89]		Laili et al. [90]	**, SO, MO-ND
Malekkhouyan et al. [33]	**, MO, V	Laili et al. [91]	
Laili et al. [24]	**, MO-ND, V	Laili et al. [92]	**, MO-ND, V
Hartono et al. [14]	**, SO, V	Zhang et al. [93]	**, SO
Hartono et al. [31]	**, SO	Zhang et al. [94]	**, MO-ND, V
Hartono et al. [4]	**, MO, MO-ND, V	Laili et al. [95]	**, MO-ND, V
Laili et al. [30]	**, SO, V	Xu et al. [96]	**, MO-ND, V
Laili et al. [91]		Qin et al. [97]	**, MO-ND, V

(continued)

Table 1 (continued)

RDSP		RDLB	
Author(s)	Method	Author(s)	Method
Laili et al. [92]	** , MO-ND, V	Liu et al. [16]	** , MO, V
Ye et al. [98]	** , SO, V		
Prioli et al. [99]			
Yang et al. [100]	** , SO, V		
Liu et al. [101]	** , SO, V		
Cui et al. [102]	** , SO, V		

Note ****** metaheuristic, V = performance measurement, **bold** = sustainability-related objective

3 Literature Connections: Bibliometric Approach

This section explores the connection between RDSP and RDLB using VOSviewer [103] for bibliometric analysis to demonstrate their interrelations. It allows for various analyses, including keyword analysis, which examines keyword occurrences in the dataset. Out of a total of 378 keywords, 50 meet the predefined threshold (3 co-occurrences). These keywords are classified by their relational strength calculated by the system into four clusters: disassembly sequence, disassembly line balancing, robot, and robot system. Additionally, the trend shift in research focus towards energy-related aspects, multiobjective optimisation, and the utilisation of AI techniques such as deep learning and reinforcement learning is evident when examining the timeline representation in Fig. 1. The co-citation with unit analysis of the cited authors reveals that among the 1389 authors identified in the literature forty-five meet the minimum citation threshold of 20 for co-citations. Four prominent author clusters were identified, with S M Gupta having the highest number of citations (159), followed by D. T. Pham (114), Q. Liu (78), and M. C. Zhou (74). In terms of geographical distribution, the research is led by the United Kingdom (UK) and China, indicating their significant contributions to this field and their connections through joint research. The bibliometric results confirm the findings of the literature review.

4 Conclusion

This study establishes a connection between the RDSP and RDLB research areas, identifying trends through an extensive literature review and bibliometric analysis. The identification of gaps in RDSP, such as the absence of sustainability objectives, multiobjective nondominated approaches, and comprehensive disassembly output, underscores the potential for further advancements. Concurrently, the lack of AI and deep learning applications in RDLB provides a promising avenue for future

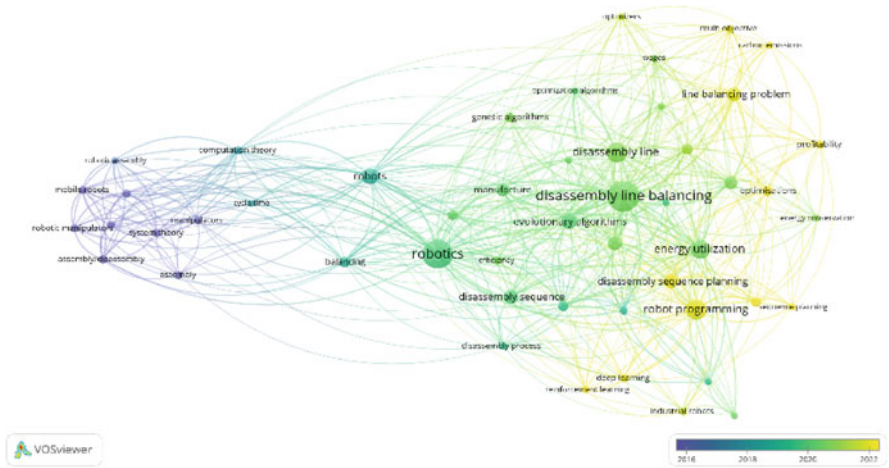


Fig. 1 Keyword analysis with timeline

research. Additionally, exploring more complex line-balancing types could be of interest. The study showcases the widespread utilisation of metaheuristic approaches in both RDSP and RDLB, validating their efficacy in addressing complex optimisation challenges. Moreover, the emphasis on performance metrics in RDLB highlights the importance of robust evaluation criteria for comparing algorithm results.

The implications of this research are twofold: first, it provides a reference for scholars interested in RDSP and RDLB, facilitating further investigations in these areas. Second, identifying research gaps and future directions motivates researchers to explore novel solutions and approaches that align with the evolving demands of sustainable remanufacturing.

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Appendix

Link to detailed tables and VOSviewer results: <https://doi.org/10.25500/edata.bham.00001002>.

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The Role of Simulation-Based Optimization in Remanufacturing and Reverse Logistics: A Systematic Literature Review



Laura Monferdini , Benedetta Pini , Letizia Tebaldi ,
Barbara Bigliardi , and Eleonora Bottani 

Abstract This paper deals with a comprehensive literature review on the topics of remanufacturing and reverse logistics, with a specific focus on the usage of computer simulation and optimization techniques. When dealing with the management of backward flows, challenges such as product complexity and variability, uncertainty in demand and supply, and high logistics and operational costs exists; to tackle these issues, strategies and techniques for optimizing processes have been explored; computer simulation was demonstrated to be a powerful tool for facing these issues. A total of 77 documents published from 2018 to 2023 are analysed, using advanced bibliometric and network analysis techniques. Outcomes highlight the challenges and opportunities associated with remanufacturing and reverse logistics and emphasise the role of simulation-based optimization in enhancing the efficiency and effectiveness of remanufacturing operations.

Keywords Remanufacturing · Reverse logistics · Computer simulation optimization · Literature review

1 Introduction

Remanufacturing is defined as the process of bringing used products to a “like-new” functional state [1]; depending on their status, these items can be put back into the market (if the product was at its end-of-life), or return to the customer’s hands in case a problem has occurred within the warranty period. According to its definition, remanufacturing can be considered a strategy both for the sustainable development [2] and environmental reasons, and for marketing [3] from the companies side, since consumers motivated by green purchases or by savings may consider remanufactured items, as also emerged from recent marketing analyses in the smartphone [4] or in the

L. Monferdini (✉) · B. Pini · L. Tebaldi · B. Bigliardi · E. Bottani
Department of Engineering and Architecture, University of Parma, Parco Area delle Scienze 181/
A, 43124 Parma, Italy
e-mail: laura.monferdini@unipr.it

automobile parts fields [5]. For completeness, for an overview of consumer behavior towards remanufactured products readers can refer to [6]. The question is: when products come to their end-of-life or need to be repaired, how do they reach the industrial plants? How is the return flow managed? The reverse logistics (RL) comes to our aid, whose formal definition is the following: the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods, and related information from the point of consumption (i.e., mainly the customer) to the point of origin (i.e., mainly the production plants) for the purpose of recapturing value or for proper disposal [7]. In case the subject that remanufactures the product is the same who produced it, the RL allows the supply chain to be defined a Closed-Loop Supply Chain (CLSC) [8]; otherwise, it is meant a Reverse Supply Chain (RSC). Nowadays, the presence of a RL channel is considered a real service from the consumer side [9], and it represents a competitive advantage, even resulting in servitization, i.e., offering integrating services in the business operations of manufacturing companies [10]. According to what has been said so far, it can be stated that remanufacturing and RL are somehow complementary: without a proper RL channel, items could not be subjected to remanufacturing as they could not reach manufacturing plants. Implicitly, also RL allows for achieving a circular economy [11]. However, the management of backward flows is anything but simple, given the fact that the integration of recovery processes into the supply chain complicates the production planning and the inventory management [12], the organization of transports and collection centers [13], the quality controls and in general it is onerous in economics terms [14]. For these reasons, several studies deal with strategies for optimizing such flows, and above all simulation was demonstrated to be a powerful tool when analyzing similar issues, related to inventory management, logistics and supply chain design [15]. Computer simulation allows for modelling and analysing the complex and dynamic processes involved in remanufacturing and RL, including disassembly, cleaning, testing, repair, and assembly [16]. Simulation and optimization can help identifying the optimal configurations of facilities, machines and workers, as well as the best policies for inventory management, production planning, and transportation scheduling. Moreover, simulation and optimization enable real-time monitoring, control, and adaptation of remanufacturing operations, based on the changing demands and resources. It is important to note that, despite the growing importance of RL and remanufacturing issues, scientific literature dealing with the use of optimization and simulation tools in these areas is surprisingly scarce. According to that, the present study aims to fill this research gap by providing an in-depth overview of the applications, trends and challenges associated with these methodologies in these contexts. To achieve this aim, results from a Systematic Literature Review (SLR) carried out on 77 scientific documents retrieved from the Scopus database are here presented, whose focus is on simulation and optimization of RL channels for remanufacturing purposes. Bibliometric analysis was performed on the sample using the *bibliometrix* package of the R software [17]. The article is structured as follows: in the following section, the methodology adopted is explained. Then, the achieved results are presented and finally a comprehensive discussion is provided.

2 Objective and Methodology

The aim of this study is to provide a thorough and comprehensive overview of the existing scientific literature on the topic of remanufacturing and RL/supply chain, with a specific focus on the usage of computer simulation and optimization techniques. To accomplish this aim, the authors conducted an analysis of the existing scientific literature, employing a systematic review methodology. This approach is recognized for its rigorous, transparent, and replicable process [18], enabling the identification of significant research patterns pertaining to the chosen topic. Consequently, the outcomes of this study are more dependable, enabling the formulation of sound conclusions and informed decision-making [19]. To carry out this study, the authors performed a computer search on the Scopus database to identify documents published from 2018 to 2023 on the topic being researched. An appropriate query was made for retrieving the relevant studies, by combining two sets of search keywords. The query structure was as follows: (TITLE-ABS-KEY (“*remanufact**”) AND TITLE-ABS-KEY (“*reverse logistic**” OR “*reverse supply chain**”) AND TITLE-ABS-KEY (“*comput**” OR “*simulation**”)). An initial set of 279 papers was obtained from the query. The year of publication of document was then limited from 2018 to 2023. The logic behind this constraint is that limiting the search to the last five years provides access to the most recent and up-to-date information on the topic in question and could contribute with a more accurate perspective on current practices and developments, thus ensuring the validity and relevance of the arguments. After this temporal constraint, 77 documents were returned, which compose the final sample. Note that the query was performed in April 2023, and accordingly year 2023 is only partially included.

3 Results

In this section, the results obtained from the review of the selected available scientific literature are provided and discussed.

3.1 Descriptive Analysis

This subsection presents a comprehensive examination of the outcomes derived from the descriptive analysis performed on the sample of 77 articles. This analysis was performed using the *bibliometrix* package of the R software [17]. The statistical analyses undertaken aim to provide insights into key inquiries, including the identification of prominent authors, the assessment of countries exhibiting significant levels of interest, and the determination of the primary journals responsible for publishing articles pertaining to the subject matter of interest. Table 1 shows the

journals that have published at least three articles in the field of this research. It turns out that *Journal of Cleaner Production* is the journal with more publications (5), followed by *Computers & Industrial Engineering* and *Sustainability*, both with 3 publications each. *Journal of Cleaner Production* represents a platform for discussion spanning several areas, including business strategy and management, environmental science, industrial and manufacturing engineering, as well as renewable energy and environmental sustainability. This journal serves as a valuable source of information regarding business management strategies and practices aimed at improving environmental performance in the context of remanufacturing. On the other hand, *Computers & Industrial Engineering* merges research in industrial engineering with computer science, thus providing an opportunity for in-depth study of optimization techniques based on algorithms, mathematical models or simulation tools applicable to the remanufacturing process. This journal provides a discussion space for topics involving general engineering and computer science, both of which are relevant in the context of optimization of remanufacturing operations. Finally, the multidisciplinary approach taken by *Sustainability* reflects the importance of considering sustainability from a holistic perspective, addressing related challenges and issues in an integrated manner. The articles published by this journal can make significant contributions to assessing the environmental impact of optimization decisions in the specific context of remanufacturing.

Figure 1 shows the distribution of papers by country of origin. The territory with the greatest number of authors is China (14) followed by India and Saudi Arabia, with 11 and 4 papers respectively. China is now the world’s largest manufacturing economy, and for this reason how to optimize the structure of the manufacturing industry and to promote innovation capability have become key issues for the sustainable development of its manufacturing industry [30]. Remanufacturing auto parts is one of the most successful businesses in the Indian scenario [31]. India is well endowed with both technology and human resources. Despite this, the concept of RL is yet not widely accepted because of many barriers for its successful implementation [32]; at the same time, remanufacturing in India is motivated by the potential profit [33].

Finally, an in-depth analysis is proposed regarding the most prominent authors (Fig. 2). Specifically, only two authors emerge: Gupta S. M. and Alqahtani A. Y. with, respectively, 5 and 3 publications on this topic. It is worth noting that these two authors have contributed to three articles on remanufacturing techniques for products with warranty policies (i.e., [34–36]).

Table 1 Most relevant source (implemented with bibliometrix on R software [17])

Journals	N. of documents	References
Journal of Cleaner Production	5	[20–24]
Computers and Industrial Engineering	3	[25–27]
Sustainability (Switzerland)	3	[14, 28, 29]

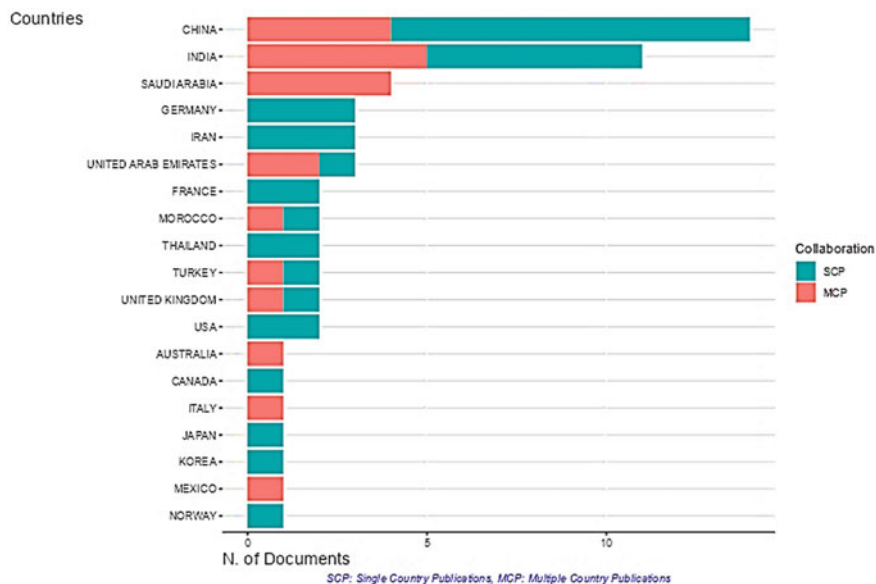


Fig. 1 Distribution of papers by country (implemented with *bibliometrix* on R software [17])



Fig. 2 Most relevant authors (implemented with *bibliometrix* on R software [17])

3.2 Systematic Literature Review

This section delves into the findings derived from the SLR, which are organized into two subsections. The first subsection identifies the classification of the topics addressed, specifically remanufacturing, RL, RSC, and CLSC. The second subsection explores the methodologies employed in the 77 papers, encompassing simulation, statistical analysis, mathematical methods, qualitative studies, and the optimization techniques utilized by the authors to obtain their respective results.

Topic Classification

Remanufacturing. Remanufacturing is the restoration of used or end-of-life (EoL) products to like-new performance [37, 38], through a series of operations such as disassembly, reprocessing, and reassembly [39]. The advantages encompass minimizing consumption and maximizing the utilization of virgin materials and energy,

while also contributing to the economic development and the creation of highly skilled job opportunities [40]. However, remanufacturing systems are subject to high costs associated with production activities due to RL, inspection and maintenance costs [41], and high degrees of uncertainty, such as market demand for remanufactured product and missing information. It is demonstrated, however, that material cost savings through regeneration can reduce the production costs of new products by 40–65% [42].

Reverse Logistics. Increased efficiency in production and supply chains in recent decades have led to increased supply and expanding markets. As a result, products are more and more accessible to a wider segment of the population. Therefore, the importance of RLs has increased significantly in recent years as it facilitates the retrieval of products and materials from the end customers by redirecting them to various stages of the supply chain. This allows multiple potential EoL scenarios to be explored, including reuse, repair, remanufacturing, and recycling [43]. Studies conducted in Europe show that every year, one European discards about 15 kg of electrical and electronic equipment [44] and this is the reason why many studies investigate RL in the electronic industrial sector. The use of RL is mainly due to two reasons; on the one hand, there are financial benefits that come from including product recovery through the introduction of RL in the production process [45]. On the other, legislation in some countries requires companies to reduce the generated waste stream from their products. In these cases, RL is not a choice, but an obligation [46].

Reverse Supply Chain. The supply chain exerts a significant impact on economic development [47], thereby garnering substantial attention from scholars [48]. Sustainable practices allow to promote economic growth [49, 50], and social improvement [51], decreasing pollution and environmental degradation that is becoming increasingly severe in some weights [52]. RSC is a prerequisite for successful, efficient planning and management in remanufacturing [53]. An RSC consists of all the parties and processes involved in collecting products from a customer to recover value or dispose them of [54]. It begins with the return of EoL products from the end customers and progresses through retailers and dealers to determine actions regarding replenishment, reconditioning, parts recovery, and scrapping [55].

Closed-Loop Supply Chain. CLSC include the activities of traditional upstream supply chains as well as those of downstream supply chains. Allowing used products to be taken back from customers and re-using the entire product, modules, parts and components to recover the value added is the focus of CLSCs [46]. The additional activities are the acquisition of products from the customers, the shipment of returns to the service facilities, the determination of the return's quality condition, the remanufacturing and the remarketing [56].

Optimization Techniques

Mathematical Model. Mathematical methods play a crucial role in addressing the complexities of RL, RSC, and CLSC. In this study, different mathematical models and software tools were investigated to address the challenges of optimization and decision making in these domains. Fuzzy logic, a powerful mathematical framework for managing the non-statistical imprecision and uncertainty of the “real world” [57],

has been used to capture the indeterminacy and ambiguity inherent in certain variables and parameters in the context of RL and CLSC operations because of its ability to handle subjective human judgments [58]. This model allowed [59] to design a multi-stage RL network for product recovery and minimize total costs. Karmakar et al. [21] considered some financial constraints of industrial management and studied the flexibility of different cost vectors by means of the triangular dense fuzzy block set rule (TDFLS) along with its ability to lock and unlock for final decision making. Mixed Integer Linear Programming (MILP) was used to account for discrete decisions such as resource allocation or determination of optimal routing paths. This technique makes it possible to determine the optimal locations and capacities of various nodes such as inspection centers and regeneration facilities and to help decision makers find optimal transport decisions and determine the number and type of transport units required in the network [25]. System Dynamics (SD) modeling, a powerful approach for studying dynamic systems, was employed to capture the interdependencies and feedback loops inherent in CLSC systems [60]. This model enabled the examination of the long-term effects of product return policies and other decision variables on system performance. By simulating the interactions among different components of the system, it provided insights into the system's behavior and identified leverage points for performance improvement [41]. To implement and solve these mathematical models, the GAMS software (General Algebraic Modeling System) was used [61]. GAMS provided a robust platform for formulating and solving complex mathematical optimization problems. Its flexibility and computational efficiency allowed researchers to translate the mathematical models into an implementable form and find optimal solutions for the considered problem instances.

Qualitative Study. Some studies contribute to the understanding of RL and remanufacturing by examining the potential for more fundamental information exchange. Through interviews with stakeholders and experts, the authors were able to assess the current state of information exchange [53] and evaluate the shortcomings and requirements of the remanufacturing market [62]. Using qualitative research methods, these studies provide valuable insights that have allowed them to explore implications for the remanufacturing of high-value parts in the RL supply chain [63].

Simulation Model. Simulation is a powerful technique used to replicate real-world systems and processes in a highly flexible virtual environment. It enables the modeling, analysis, and optimization of complex systems [54], representing various configurations, such as RL and remanufacturing, by mimicking their behavior and evaluating different scenarios. For example, Arena allows the creation of dynamic models [64] to analyze system behavior, optimize it, and predict the warranty period to assign to each disassembled component and regenerated product [34, 64]. The Multi-Agent System (MAS) simulation approach reproduces the behaviors and interactions of individual agents to simulate complex logistics networks accurately, overcoming the inherent intractability of models attempting to capture the dynamics of complex networks [65]. Rachih et al. [12] addresses an inventory control model for a RL system that manages two types of demand: one for new products and the other for remanufactured products, which have different selling prices. To minimize the total cost, the study utilized discrete event simulation (DES) integrated with OptQuest

software. This integration provided optimization capabilities to enhance the performance of RL and remanufacturing processes by determining the optimal allocation of resources and decision policies.

Statistic Analysis. Statistical techniques provide valuable insights, enable data-driven decision-making, and help optimize processes in the context of RL, CLSC, RSC and remanufacturing. To improve decision-making processes by incorporating probabilistic information, updating parameters, and estimating uncertainties in the context of remanufacturing, the Bayesian approach can be applied [66]. As previously mentioned, the supply chain (SC) is a highly complex and dynamic system. Statistical techniques such as bifurcation diagram, maximum Lyapunov exponent, price power spectrum, and so on [67], aid in understanding the dynamic behavior, predictability, and stability of the pricing game model, taking into account the changeable behavior of recyclers. Analysis of Variance (ANOVA), specifically, can be employed to assess the performance of a stochastic inventory model for a hybrid manufacturing-remanufacturing system and help determine the significance of different factors affecting the system's performance and identify optimal strategies for inventory management [68]. Furthermore, the incorporation of flexible capacity in the planning of a multi-product multi-echelon sustainable RL network can be achieved through the utilization of Mixed Integer Programming (MIP) and Pareto analysis. MIP facilitates the optimal allocation of resources and informed decision-making, while Pareto analysis enables the identification of trade-offs and the attainment of a harmonious balance among diverse objectives during the network design process [24].

4 Discussion and Conclusion

This paper presented the results of a SLR conducted on the topic of remanufacturing, RL, RSC and CLSC channels, with a specific focus on the usage of computer simulation and optimization techniques. The objective of the study was to provide a comprehensive overview of the existing scientific literature in this field. The study identified a total of 77 relevant scientific documents published between 2018 and 2023. Descriptive analysis revealed key insights into prominent authors, countries of origin, and journals that have contributed significantly to the research on remanufacturing and RL. The distribution of papers by country showed that China had the highest number of authors, followed by India and Saudi Arabia. This reflects the growing interest and importance of topics in these countries, driven by factors such as the sustainable development of China's manufacturing industry and the potential for profit in remanufacturing auto parts in India. These topics were explored using various methodologies, such as mathematical modelling and optimization techniques, including fuzzy logic, MILP, and SD modelling, that were frequently employed to address the complexities of RL and supply chain operations. Overall, the findings of this study highlight the importance of these techniques in identifying the optimal configurations of facilities, machines, and workers, as well as in developing

effective policies for inventory management, production planning, and transportation scheduling. Additionally, simulation and optimization enable real-time monitoring, control, and adaptation of remanufacturing operations based on changing demands and resources.

The results of this SLR contribute to the existing body of knowledge on remanufacturing and RL, providing valuable insights for researchers and practitioners in the field. In this study, a single database was utilized to construct the sample of items under investigation, thus it is recommended for future research to concentrate on optimizing remanufacturing processes by employing diverse databases and delving into the subject matter through the analysis of select case studies.

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Exploring Industry 5.0 for Remanufacturing of Lithium-Ion Batteries in Electric Vehicles



Alessandro Neri , Maria Angela Butturi, Leandro Tomasin da Silva,
Francesco Lolli, Rita Gamberini, and Miguel Afonso Sellitto

Abstract The growing demand for electric vehicles exacerbates concerns over the environmental implications of lithium-ion battery waste, which poses risks to both ecological systems and public health. While remanufacturing has been acknowledged as a viable, sustainable pathway for mitigating these issues, existing literature lacks a comprehensive investigation into the role of Industry 5.0 technologies in optimising this process. To achieve this goal, this study compares and evaluates the potential of different Industry 5.0 technologies and approaches to support the remanufacturing process of lithium-ion batteries. Specifically, we apply the AHP-PROMETHEE method to identify the most critical and influential Industry 5.0 prospects that should be prioritised for development and implementation. The novelty of our approach lies in the identification of critical Industry 5.0 imperatives that can enable efficient and effective remanufacturing processes. The analysis is supported by a comprehensive review of the relevant literature. The results of our study provide important implications for policymakers, battery manufacturers, and remanufacturing companies. By prioritising key Industry 5.0 technologies like digital twins, the Internet of Everything, and blockchain, this study shows that carmakers can significantly improve efficiency and sustainability in battery remanufacturing. This paper contributes to

A. Neri (✉) · F. Lolli · R. Gamberini

Department of Industrial Engineering, University of Bologna, Via Zamboni, 33, 40126 Bologna, Italy

e-mail: alessandro.neri@unimore.it

M. A. Butturi

Department of Science and Methods for Engineering, University of Modena and Reggio Emilia, Piazzale Europa 1, 42100 Reggio Emilia, Italy

L. T. da Silva · M. A. Sellitto

Production and Systems Engineering Graduate Program, Universidade do Vale do Rio dos Sinos, Av. Unisinos 950, São Leopoldo 93022-000, Brazil

F. Lolli

En&Tech Interdipartimental Center, University of Modena and Reggio Emilia, Via Amendola 2, 42122 Reggio Emilia, Italy

R. Gamberini

InterMech MO.RE. Interdepartmental Centre, University of Modena and Reggio Emilia, Via Amendola 2, 42122 Reggio Emilia, Italy

the emerging research on the integration of Industry 5.0 technologies in the remanufacturing process of lithium-ion batteries. Our next step is to explore the potential of the identified technologies in real-life applications and to evaluate their impact on the sustainability and efficiency of the remanufacturing process of lithium-ion batteries.

Keywords Lithium-ion batteries · Remanufacturing · Industry 5.0 · Sustainability · MCDM · Automotive

1 Introduction

The increasing demand for electric vehicles (EVs) has resulted in a surge in the production of lithium-ion batteries (LIBs). However, the disposal of these batteries at the end-of-life (EOL) presents significant environmental challenges due to their hazardous components, including heavy metals and toxic chemicals. To address this issue, remanufacturing has emerged as a promising solution to mitigate the environmental impact of LIB waste by recovering and restoring used batteries, thereby extending their life cycle [1]. Furthermore, remanufacturing can contribute to reducing the production of new batteries, thereby minimising the environmental impact of the LIB market [2]. However, there is a notable gap in the existing literature concerning how advanced technologies, specifically Industry 5.0 (I5.0) enablers, can optimise the LIB remanufacturing process.

Industry 5.0 (I5.0), which represents the convergence of industrial automation, digital technologies, and human worker inclusion, has the potential to revolutionise the remanufacturing process of LIBs. Leveraging I5.0 enablers such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics can enable more efficient and effective processes, leading to reduced costs and improved sustainability [3]. By embracing an I5.0 approach, remanufacturing companies can optimise their operations and minimise waste, while battery manufacturers can gain a competitive advantage by offering more sustainable products.

The purpose of this paper is to explore the potential of I5.0 for supporting the remanufacturing of LIBs from EVs. The objectives of this study are as follows:

1. Understand the current state of LIB remanufacturing and the challenges it faces.
2. Explore the potential of I5.0 technologies for enhancing the remanufacturing process.
3. Prioritise I5.0 approaches in the remanufacturing process.

By achieving these objectives, this research aims to shed light on the opportunities offered by I5.0 for improving the remanufacturing of LIBs, thereby contributing to sustainable manufacturing practices and the circular economy.

The remainder of this paper is organised as follows: Sect. 2 offers a comprehensive background on LIBs and I5.0, laying the groundwork for the subsequent analysis. Section 3 outlines the methodology, detailing how the AHP-PROMETHEE method

is employed to evaluate and prioritise Industry 5.0 technologies for LIB remanufacturing. Section 4 presents the study's findings. Finally, Sect. 5 summarises key takeaways and suggests avenues for future research.

2 Literature Review

2.1 *Remanufacturing of Lithium-Ion Batteries*

The rapid growth of the EV market fosters a correspondent fast rise in battery utilisation, posing material shortages and rising material price issues, as well as EOL concerns. According to the mainstream literature, batteries used in mobility applications generally reach the end of their lifespan when their energy capacity drops to around 80% of the initial capacity after 5–10 years of service, although improved LIB technologies suggest that this threshold can be overcome [4]. It is estimated that, by 2030, there will be 100–200 GWh of LIBs that will end their automotive life [5]. To optimize resource use and minimise waste by applying circular economy principles, an increasing number of LIBs will become available for post-first-life applications, including re-use, remanufacturing, and recycling [6]. Re-use can include both the reapplication in electric vehicles and the repurposing for non-automotive applications (usually stationary use), while recycling allows for the return of valuable materials back into the value chain; remanufacturing is the intermediate option between the previously mentioned [7]. Remanufacturing prioritises the finished product as opposed to refurbishment or retrofit, which focus on exchanging, modernising, or repairing individual components; some studies show that remanufacturing is economically feasible, saving about 40% compared to using new batteries (see for example [8]). Remanufacturing is the process of restoring LIB so they can be used in their original (automotive) applications. To pass a remanufacturing process, the batteries must present good health (SOH) and satisfy all OEM specifications for power, energy, cycle life, etc. Refer to Table 1 for a brief description of remanufacturing challenges.

Diagnostic testing, partial disassembly of the battery packs, replacement of any damaged cells or modules, and final reassembly into new battery packs are the main steps in the remanufacturing of LIBs. Due to the risks involved in handling hazardous chemicals, the logistics for the removal and collection of the used LIBs towards the refurbishment centres require safe handling and storage [1].

The testing methodologies include the estimation of SOH, which is commonly done by measuring various parameters such as impedance and internal resistance. These parameters provide insights into the degradation mechanisms that occur during battery ageing [10]. Since the diagnostic step is complex and time-consuming, and to ensure that the batteries can be used to their maximum lifetime possibilities, data-based methods applying machine learning techniques (such as cloud-based methods and digital twins) to data obtained by sensors already installed in the battery systems seem to be the most advantageous methods to calculate the SOH and expected lifetime

Table 1 List of LIBs remanufacturing challenges

Notation	Challenges	Options	Refs.
C1	Different shapes and features hinder standardized remanufacturing	Design for remanufacturing, considering modularity and disassembly	[6, 9]
C2	Safe handling (take-back logistics)	Labelling system, RFID	[1]
C3	Time and resources consume diagnostic and battery status tracking	Data-based machine-learning methods (cloud-based, digital twins) using existing sensor data	[7, 10]
		Battery passport based on blockchain technology	[5]
C4	Safe and economic disassembly	Robotic disassembly with cloud computing support and human-machine hybrid mode; Virtual disassembly	[5, 11, 12]
C5	Reassembly	Original manufacturers involvement	[13]

of the devices, reducing costs and improving the remanufacturing process. By making these data accessible via blockchain technology, the European Commission’s plan to create a “battery passport” might be put into practice [5, 7].

The disassembling process can be split into stages, such as opening the battery pack’s shell (in a controlled atmosphere to minimise oxidation at the cathodes), removing the mechanical and electrical connections between the cells, and removing auxiliary electronic components. The disassembly process is typically dangerous and calls for skilled specialists and specialised equipment. Robotic battery disassembly supported by cloud computing or a human-machine hybrid disassembly mode may reduce the chance of a human accident while simultaneously cutting remanufacturing costs [5, 11]. Moreover, virtual disassembly can help in optimising the procedures and identifying the “stopping point” of the operation that maximises profitability [12]. To address battery type variability and standardise the remanufacturing process, it is necessary to create integrated designs for the LIBs parts that take modularity, interfaces, and disassembly into account [6, 9].

The replacement of damaged components and final reassembly are steps that remanufacturing shares with the manufacturing process, for which the original production facility could be employed. This highlights the importance of building a proper circular business model, involving the original battery manufacturers and the main stakeholders in the EV value chain [13].

2.2 Prospects of Industry 5.0

To fully comprehend the benefits of I5.0, it is essential to first understand the foundation laid by Industry 4.0 (I4.0). I4.0, which was first presented in Germany, is described as the use of Cyber-Physical Systems (CPS) to gain a competitive edge in manufacturing processes [14]. It leverages digital technologies and automation to create smart factories, building upon the advancements of the internet. Key concepts include digitization, the IoT, cloud computing, robotics, automated manufacturing, and AI [15, 16].

I4.0 and I5.0 represent intertwined stages of industrial development. While I4.0 primarily focuses on technological innovation and digital transformation, I5.0 expands upon this by incorporating resilience, sustainability, and human-centricity concepts [17]. I5.0 “complements the existing I4.0 paradigm by having research and innovation drive the transition to a sustainable, human-centric, and resilient European industry”, according to the European Commission [18]. It emphasises the collaboration between human workers and robots, leveraging human intelligence and creativity [19]. Furthermore, I5.0 also preserves the environment by making more precise decisions using predictive analytics and operational expertise [20], while fostering digital and green transitions [21]. I5.0 places the well-being of industry employees at the centre of production, emphasising a human-centric and sustainable approach to industrial growth [22]. Future factories should enable and empower human operators physically and intellectually, while robots assist with physically demanding tasks, cognitive systems provide decision-making advice, mixed reality enhances human vision and decision-making, and co-intelligence involves humans supporting robots and vice versa [23].

Table 2 provides a comprehensive list of enabling technologies for I5.0, highlighting their respective benefits and references.

The table of enabling technologies for Industry 5.0 highlights several key insights. Firstly, Industry 5.0 requires a holistic approach to technological integration, focusing on objectives [23], which is more than early modularity approaches [38]. Secondly, Industry 5.0 uses technology to achieve sustainability and resource efficiency [39]. Lastly, Industry 5.0 combines human expertise with robotics to improve decision-making [33]. Technology integration, sustainability, and human capabilities are essential for I5.0.

3 Methodology

This study introduces a model using I5.0 technology to address upcoming challenges in EV exhaust battery management within the automotive sector’s circular economy. By performing an exhaustive lit review, the paper identifies primary issues in LIB remanufacturing and prospective I5.0 solutions. The AHP-PROMETHEE method is

Table 2 List of I5.0 enablers and prospects

Notation	I5.0 enabler	Prospect	References
A1	Additive manufacturing (AM)	Precision manufacturing with minimized waste and resource optimization	[24, 25]
A2	Predictive maintenance (PM)	Identifies and prevents equipment issues, optimizing sustainability and efficiency	[24]
A3	Cognitive cyber-physical systems (CCPS)	Real-time adaptation to demand changes, agility, and intelligence	[24]
A4		Strengthens human cognition for safer man-machine symbiosis	[26]
A5	Cloud manufacturing (CM)	Global collaboration and resource sharing, decentralization, and cooperation	[24]
A6		Strategic placement of manufacturing units and optimal location of plants near raw materials, and low costs	[27]
A7	Collaborative robots (Cobots)	Positive human-robot relationship, performance optimization, and risk reduction	[24, 28]
A8	Blockchain technology (BT)	Decentralized trust, secure transactions, transparency, and streamlined processes	[24]
A9		Enables secure digital identities, like product life-cycle data management	[28]
A10	Virtual and augmented reality (VR/AR)	Improved skill development and precision in inventory management	[27, 29]
A11		Enhances real-time information transfer and quality control providing flexible operations and technical advice	[28, 30]
A12	Next-gen wireless networks (5G/6G)	Faster, more reliable, more efficient communication, and seamless connectivity	[27, 31]
A13	Smart wearables (SW)	Improved productivity and worker safety in a human-centric environment	[26]
A14	Industrial metaverse (IM)	Bridging real and virtual worlds for interaction and influence	[32]
A15	Bio-inspired technologies (BIT)	Sustainable and smart material usage, and recyclability	[33, 34]
A16	Digital twin (DT)	Online emulation tool for system redesign, reconfiguration, and optimized operation	[28]
A17	Edge computing (EC)	Offloading tasks from the cloud to IoT devices at the network edge	[35]

(continued)

Table 2 (continued)

Notation	I5.0 enabler	Prospect	References
A18		Low latency, high-quality services, extensive IoT infrastructure, and integrated AI	[36]
A19	Internet of everything (IoE)	Holistic connectivity and total integration for efficient decision-making	[24, 37]

applied to prioritise the development of an I5.0 supply chain for LIB remanufacturing. The paper concludes with an analysis of the results and managerial implications.

3.1 Data and Context of Study

During the data retrieval phase, a systematic effort was made to gather relevant information on LIBs remanufacturing and the implementation of I5.0 techniques. This approach allowed for a comprehensive understanding of the key challenges, opportunities, and risks associated with implementing remanufacturing processes for LIBs in the automotive industry, as well as the potential of I5.0 in addressing these issues. Five critical criteria were identified to assess the effectiveness of I5.0 prospects. Expert surveys were conducted, involving 7 specialists with expertise in I5.0, LIB remanufacturing, and relevant experience. The specialists evaluated and rated the identified I5.0 imperatives presented to them in a questionnaire. Table 3 shows a brief description of expert profiles.

The AHP method will be employed to determine the weights of remanufacturing issues based on professional assessments, providing a foundation for

Table 3 Experts detailed information

Features			Sample	Percentage (%)
Evaluators (=7)	Role	Managing director	1	14.300
		SC manager	3	42.850
		Academic	3	42.850
	Designation	Sustainability	2	28.575
		Logistics	2	28.575
		Operations	3	42.850
	Experience	<5 years	2	28.575
		5–10 years	2	28.575
		>10 years	3	42.850
	Gender	Male	4	57.150
		Female	3	42.850
		Other	0	00.000

analysing the effectiveness of various I5.0 schemes in addressing these challenges. The PROMETHEE approach will utilise the criterion weights to rank and evaluate different I5.0 areas of interest. The results of the analysis will assist policy-makers, automakers, and stakeholders in prioritising I5.0 imperatives and developing sustainable plans for LIBs remanufacturing.

3.2 *Hybrid AHP-PROMETHEE*

This article proposes a hybrid model that combines the Analytic Hierarchy Process (AHP) and the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) to address the multi-criteria decision-making (MCDM) problem. The AHP approach, developed by Saaty [40], establishes a hierarchical model where pairwise comparisons determine the relative importance of criteria and alternatives are evaluated to calculate overall performance scores [2]. AHP excels at handling complex, multi-criteria decisions. It offers a consistency check for reliable criteria weighting and allows input from diverse stakeholders. Moreover, it's versatile, fitting various decision-making contexts.

The PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) can rank and evaluate alternatives based on multiple criteria [41], incorporating both qualitative and quantitative factors [42]. PROMETHEE is ideal for prioritising multiple alternatives. It provides a complete ranking, not just the best option. The method is transparent and user-friendly, making it accessible for both research and practice. It includes PROMETHEE I for partial ranking and PROMETHEE II for complete ranking [3]. The hybrid model begins with pairwise comparisons using an evaluation matrix, followed by assigning preference functions with values from 0 to 1. The global matrix aggregates results, forming a rank [43]. A more in-depth discussion is available in the recent literature [40, 41]. Further research should also focus on integrating multi-attribute and AI-based models, such as artificial neural networks (ANN), for consistency verification [44].

4 Results

The AHP analysis reveals that the criterion with the highest weight of 35.9% is C3, emphasising the significance of diagnostic testing and data-based machine-learning methods for extending the life of lithium-ion batteries. Following closely behind is the criterion of C4, with a weight of 28.3%, highlighting the importance of safe and cost-effective disassembly techniques. The criterion of C1 holds a weight of 18.9%, while C2 and C5 have weights of 9.0 and 7.9%, respectively. The results of the PROMETHEE analysis provide valuable insights into the potential of I5.0 prospects for addressing the challenges of remanufacturing in the automotive sector. By using a single-vote matrix, each respondent's vote was given equal significance, allowing

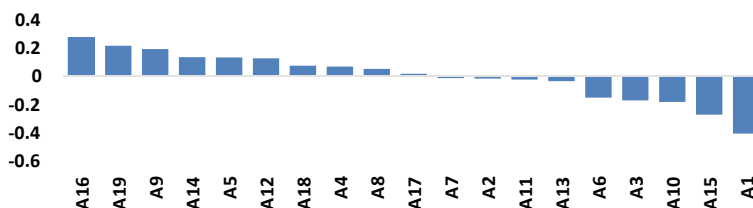


Fig. 1 Relevance of each 5.0 prospect to remanufacturing challenges

for a comprehensive evaluation of the prospects. The net outranking flow values in Fig. 1 illustrate the relative relevance of each prospect to solving the main challenges.

In the future of LIB remanufacturing, key I5.0 enablers such as DT, IoE, and BT will play a significant role. Among the prospects, A16 emerges as the top-ranked prospect with a significant positive net flow value of 0.3177. This suggests that the implementation of DT technology can greatly enhance the remanufacturing process by enabling online emulation, system redesign, reconfiguration, and optimised operation. It offers a powerful tool for improving efficiency and effectiveness in the battery remanufacturing domain. A19 also demonstrates a strong positive net flow, securing the second position in the rankings. This prospect emphasises the importance of holistic connectivity, integrating people, processes, information, and objects to facilitate efficient decision-making. By leveraging IoT technologies, A19 enables seamless integration and improved operational performance in the remanufacturing process. Furthermore, A9 foresees a cure and a transparent method for tracking the lifecycle of each battery. Then, A14 offers a virtual collaborative space where designers, engineers, and customers interact. This fosters innovation and accelerates problem-solving, leading to more efficient and customer-centric remanufacturing processes. A5 acts as a bridge, leveraging its global collaboration and resource optimisation capabilities, boosted by A12. By sharing resources and collaborating with other facilities, CM maximises the potential of wireless networks, enabling seamless connectivity and integration across remanufacturing operations. This synergy enables real-time data sharing, efficient diagnostics, and the life-extending of LIBs, contributing to the overall success of the remanufacturing process.

5 Conclusions

The implementation of I5.0 technologies presents significant opportunities for the remanufacturing of LIBs in the automotive sector. By leveraging advancements such as DT, IoE, BT, CM, and 5G/6G, carmakers can achieve efficient and sustainable LIB remanufacturing processes. These technologies enable virtual modelling, real-time connectivity, secure data management, global collaboration, and optimised resource utilisation. The integration of these technologies improves diagnostics, enhances disassembly and reassembly processes, facilitates information sharing, and supports

decision-making. Through the prioritisation of I5.0 prospects, such as A16, A19, and A9, among others, carmakers can create a comprehensive and interconnected system that drives innovation, efficiency, and sustainability in LIB remanufacturing. Combining DT, IoE, and BT into LIB remanufacturing establishes an intriguing research topic. DT provides a solid foundation for predictive analytics, allowing for proactive actions that could potentially revolutionise battery diagnosis. The capabilities of IoE in process automation and real-time data capture give up opportunities for optimising disassembly and reassembly stages, cutting expenses, and increasing efficiency. BT is a key technology for providing safe, transparent, and traceable data sharing, which is a prerequisite for scalable and sustainable remanufacturing practices. This research highlights the potential of I 5.0 in addressing the challenges of LIB remanufacturing and provides valuable insights for policymakers, automakers, and other stakeholders in developing sustainable strategies for the circular economy of the automotive sector. This study has indeed some limitations. The potential of I5.0 technologies in LIBs remanufacturing was assessed within a theoretical framework, lacking empirical validation. Future research could involve applying these technologies in real-world settings to assess their practical impact. Secondly, the focus of this study is primarily on the automotive sector, limiting its generalizability to other industries that also utilise LIBs. Future work could explore the implications of our findings in other sectors, such as consumer electronics or renewable energy storage.

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Remanufacturing Decision-Making Tools: A State of the Art



Marcello Fera, Mario Caterino, Natalia Hartono, Maria Antonietta Turino, Raffaele Abbate, Pasquale Manco, Salvatore Miranda, Stefano Riemma, and Roberto Macchiaroli

Abstract In the era of the circular economy (CE), more and more attention is paid to some production strategies such as Remanufacturing. This strategy aims to promote the creation of new lives for products considered at the end of their life and, therefore, reduce the industrial impact on the sustainability matrixes. Remanufacturing has grown in importance and relevance in the last few years, especially at an industrial glance, as evidenced by the birth of numerous divisions of primary Original Equipment Manufacturers (OEM) addressing remanufacturing. In this context, problems related to the practical consequences of the decisions related to the remanufacturing processes are relevant for the industrial decision-makers. Thus, the development of tools supporting the decision-makers in the remanufacturing field has increased in the last few years. This paper contributes to the identification and selection of the most suitable decision-making methods for several specific issues of Remanufacturing. To achieve this aim, a systematic review of the international scientific literature is conducted, providing practical insights for practitioners and proposing potential directions for further research development to enhance this knowledge domain.

Keywords Remanufacturing · Decision support systems · Decision-making tools · Systematic literature review · SLR

M. Fera (✉) · M. A. Turino · R. Abbate · P. Manco · R. Macchiaroli
Department of Engineering, University of Campania “Luigi Vanvitelli”, Via Roma 29, 81031
Aversa, CE, Italy
e-mail: marcello.fera@unicampania.it

M. Caterino · S. Miranda · S. Riemma
Department of Industrial Engineering, University of Salerno, Via Giovanni Paolo II 132, 84084
Fisciano, SA, Italy

N. Hartono
University of Pelita Harapan, Tangerang 15811, Indonesia

1 Introduction

The growing awareness of the environmental impact caused by the production and consumption of materials and the introduction of stricter regulations encourage a more sustainable development that not only includes economic development, but also environmental sustainability and social stability. Manufacturing, as the foundation of industrial economies, should optimize economic benefits through better resource allocation and, at the same time, reduce its impact to achieve sustainable living. The main feature that separates sustainable products from their traditional counterparts is their multiple life cycles. When a sustainable product approaches the end of its first life cycle, it enters the post-life phase, which aims to maximize the use of the product through the application of the “5Rs”: reduce, reuse, recycle, recover and regenerate [1].

Remanufacturing or “re-manufacturing”, on the other hand, brings the used product back to conditions equivalent to or better than the original ones [2, 3]. Remanufacturing is a sustainable manufacturing practice that helps to reduce waste, conserve energy and resources, and improve the environmental sustainability of manufacturing [4]. Based on the latest studies, during the first product life cycle it is possible to optimize both the processing planning and the working conditions to reduce energy consumption and extend the life of the product [5]. Furthermore, supported by the latest studies on the matter, we can state that a remanufactured item requires about 80% less energy and about 85% less raw material than an article produced from scratch [6]. Therefore, re-manufacturing represents a broader system that allows the declination of the CE paradigm in the production plans of companies. In addition to increasing the life cycle of the product, re-manufacturing focuses on the study and implementation of new design methodologies that allow the design of goods, which can be easily repaired or reinserted into the market [7].

Given its great potential and the advantages it can bring, this practice is particularly attractive for industries that manufacture products with a high capital density and a relatively long-life cycle such as aerospace, automotive, railways, machinery, electronics, furniture, electromedical. The remanufacturing production main phases are six and they are divided as follows: (i) inspection, (ii) cleaning, (iii) disassembly, (iv) reprocessing, (v) reassembly and (vi) testing. Each one of these phases is characterized by several inputs to be assessed to decide the right quantity to be produced, the time span for production and the production rates to be met. Moreover, it is worth noting that the re-manufacturing phases are different from the traditional linear production process phases, generating further issues related to the costs and benefits that can be associated with the implementation of re-manufacturing practices in existing industrial environments. To get an idea of the complexity of the re-manufacturing process, the reader can think of the differences among returned products due to the different use conditions during their life, or to the different times needed for carrying out the same processes on returned products whose only difference is the quality. These issues inevitably impact the re-manufacturing process management, its characteristics, and its performances. In this context, the

use of decision support tools may be very important in industrial contexts to help decision-makers manage such a complex process.

So, the aim of this paper is to analyze what is the state of the art about the use of decision-making tools in the remanufacturing process management, trying to identify criticalities and possible future developments for these tools that could be implemented in the future of the remanufacturing divisions of many OEMs and industries in general. To do so, a bibliometric and Systematic Literature Review (SLR) methodology will be used. The remaining sections of the paper are organized as follows: a section about the methodology used in this paper and the main elements of the identification and selection of the papers, a section about the results of the SLR, followed by a discussion and conclusions section.

2 Methodology

In this section, the main steps conducted to carry out the SLR will be described. The Research Question (RQ) has been formulated as follows:

- What are the DSSs and tools applied in the remanufacturing context?

The data used for the study comes from selected articles on “Scopus”, a database provided by the scientific publishing editor “Elsevier”. The selection of the articles was carried out by applying inclusion and exclusion criteria to a query, specifically created on Scopus, in order to obtain the most relevant results for our research. The inclusion and exclusion criteria established to filter the articles pertain to the following aspects:

- The years of search are limited to the last 23 years because this was the time span in which the circular and sustainability concepts were first introduced;
- The selection of journals was limited to manufacturing and production engineering and production sustainability, as our objective is specifically focused on aspects related to these criteria;
- The language selected for the research papers investigated is English, due to the relevance of this language in the academic scholars involved in this research field;
- The keywords criteria were aimed at narrowing down and focusing attention on specific aspects of manufacturing, production design, and management principles, particularly in relation to their application in remanufacturing;
- The thematic area is engineering because our aim is to investigate the topic from this point of view.

After applying these criteria, the next steps were the reading of the abstracts and the reading of the complete articles in order to carry out further skimming.

The search and identification phases of the articles were accompanied by bibliometric analyses. Once the articles were collected, their study and then their analysis were carried out.

The first phase of our study consists of the creation of a query, that is a string containing Boolean operators and appropriate commands, which allowed to identify a sufficiently large number of articles and results regarding our topic. The string used in this research paper is as follows: “TITLE-ABS ((“decision support system”) OR (item AND return AND policies) OR (“decision making process”) OR (item “quality inspection”) OR (“inspection process”) OR (process) OR (“item conditions”) OR (“Inspection process”) OR (inspection)) AND AUTHKEY ((quality) OR (“decision support system”) OR (inspection) OR (process) OR (“circular economy”)) AND AUTHKEY (remanufacturing)”. The search string was run in the early 2023.

3 Results

This string led us to a preliminary result of 341 articles, written between the years 2000 and 2023, with a total of 4864 citations. Once the articles were collected, a first bibliometric analysis of the articles using the “Microsoft Excel” and “VOSviewer” software was carried out, evaluating:

- The number of articles by year;
- The number of citations by year;
- The main sources, i.e. the journals with the highest number of publications;
- The links between the keywords;
- The links between keywords by year.

The first aspect of the analysis is represented by Table 1, which presents the number of articles published per year. Additionally, Fig. 1 provides insights into the research progress over the years regarding the investigated topic.

Figure 1 shows as the trend of publications on the topic started to increase from the years 2009–2010. A sharp slowdown occurred around the years 2019–2020 but this was probably caused by the Covid-19 pandemic. Regarding the year 2023, although there are currently a small number of papers available, it is highly foreseeable that there will be a consistent increase in the volume of papers throughout the year.

Concerning the number of citations per year. Table 2 and Fig. 2 show its trend over the years.

Table 1 Number of articles per year

Year	# Articles	Year	# Articles	Year	# Articles	Year	# Articles
2000	1	2006	5	2012	9	2018	29
2001	1	2007	1	2013	15	2019	37
2002	0	2008	7	2014	24	2020	26
2003	1	2009	2	2015	19	2021	51
2004	0	2010	9	2016	18	2022	54

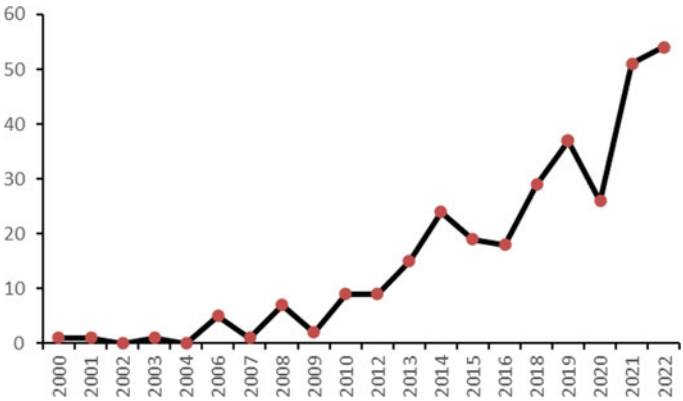


Fig. 1 Number of Articles per year

Table 2 Number of citations per year

Year	#Citations	Year	#Citations	Year	#Citations	Year	#Citations
2000	0	2006	19	2012	289	2018	736
2001	4	2007	1	2013	294	2019	905
2002	0	2008	9	2014	392	2020	339
2003	93	2009	33	2015	476	2021	295
2004	0	2010	331	2016	553	2022	95

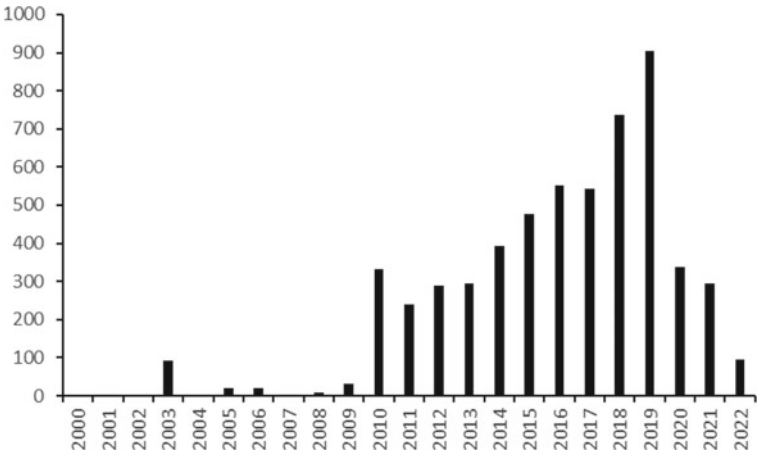


Fig. 2 Number of citations per year

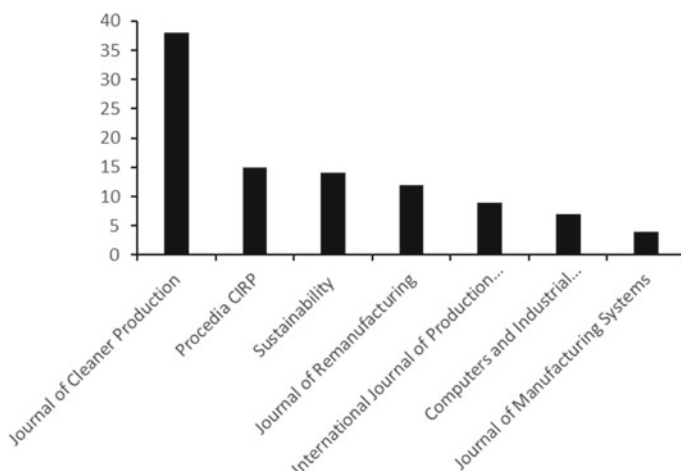


Fig. 3 Papers published per journal

Also in this case, it appears evident the poor attention to the topic before 2009. The number of citations is an expression of the attention of the scientific community towards the topic. An example is the year 2019, where, even if the number of articles is low, the citation count is high, highlighting that the topic was also analyzed in other research fields rather than only the ones embodied in this study.

Figure 3 shows the most impacted scientific journals. Most of them are related to the sustainability in production systems and to production systems in general.

Figure 4 shows the analysis of the keywords for the analyzed papers realized through VOSviewer. It is possible to identify 2 main clusters, the green one concerning sustainability and the red one concerning operations. Remanufacturing belongs to the sustainability cluster, but it is also strongly connected to the operations cluster, highlighting that this practice is seen by authors as a driver for reaching sustainability goals, but its operations must be developed as well. These themes especially arose in the last five years, as illustrated in Fig. 5, where the map is colored according to the year of appearance of the keywords. Moreover, in the last few years it is possible to look at a focus on the sustainability issues as shown from the keywords map per publishing year produced thanks to the VOSviewer, Fig. 5. This last aspect is probably due to the definition of the fundamental business and operations management models in the previous years, which give the possibility to concentrate on the more strategic aspects, following a bottom-up approach to the decision-making problems in the remanufacturing field.

The last phase of the analysis is divided into two parts which consecutively allowed to reduce the number of papers analyzed to a set of 35 articles.

Initially, the exclusion criteria were applied, eliminating 102 results, thus reaching 239 articles. Subsequently, for the remaining articles, the abstracts reading was performed, reaching 56 papers. Lastly, the full paper reading was applied, achieving

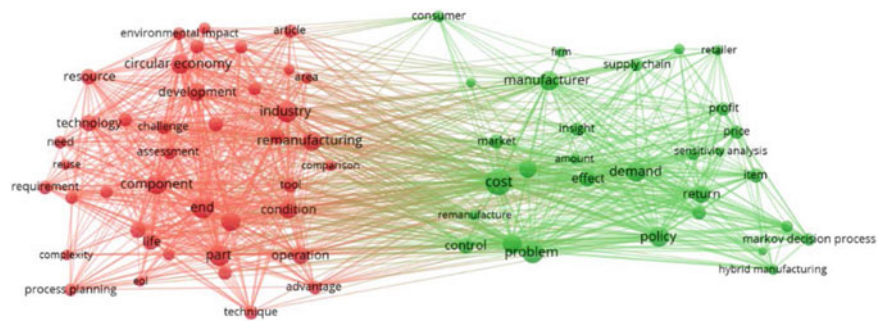


Fig. 4 Keywords map and knowledge clusters

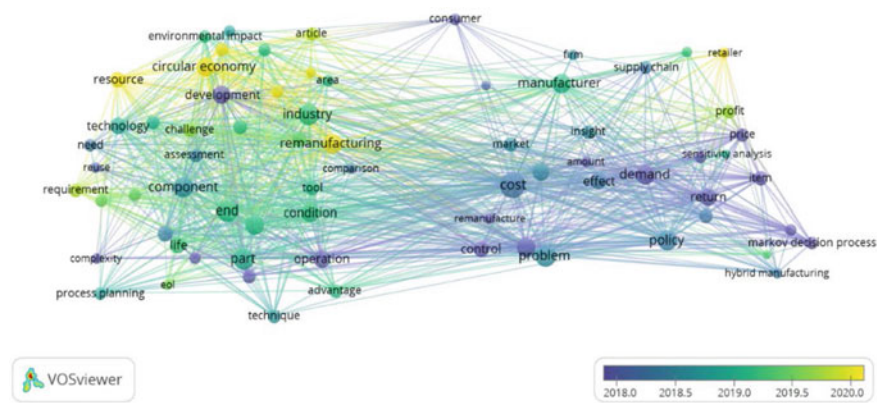


Fig. 5 Keywords map per publishing year

the final sample of 35 papers. In Fig. 6 the phases of the SLR are summarized with the relative numbers of articles identified step by step.



Fig. 6 SLR process

The analysis of the selected papers highlighted that the DSSs and the decision-making tools in general are a fundamental element of all the operations for remanufacturing phases management, in particular for the inspection and disassembly phases.

About the inspection phase, this relevance is confirmed from several literature sources such as [6, 8–19]. They all concluded that the inspection phase of remanufacturing can be enhanced by the combined use of digital sensors, decision-making software and artificial intelligence (AI). In particular, they allow for the acquisition and analysis of images, 2D and 3D CAD files and point clouds to facilitate the identification of the “fault feature”, the failure or break modes with the final objective to understand if the item can be remanufactured or not. Data acquisition is generally carried out via scanner, Red, Green, Blue (RGB) camera and depth chamber in the case of surface investigations or by means of ultrasound sensors in the case of non-destructive sub-surface investigations. For the identification of the fault features, it is possible to distinguish two main cases, one fully automated and one non-automated or partially automated.

In the first case, software, through AI [14], or a Convolutional Neural Network (CNN) [13], compares the input data with those in the historical databases. In this case, the aforementioned sensors can be connected to a robot or a robotic arm, which, by following the inspection, evaluates whether the item can be remanufactured or not; in the event of a positive outcome, by applying a Case Based Reasoning system (CBR) [16], it indicates which is the most suitable process to follow to remanufacture the article. In the event of a negative result, however, the article will be rejected. Finally, if inconsistencies should arise, human intervention will be required to solve them.

In the case of non-automated systems, men identify the features and evaluate whether the item can be remanufactured or not. The inspection phase can take place either manually [20], leaving the complete responsibility of the decisions to the operator, who will carry out the assessment based on his own experience, or in a partially automated way in which human–robot cooperation is present [21]. The human operator, therefore, will be assisted in the inspection of the features and in the subsequent decisions by robots and, through a Graphical User Interface (GUI), the operator can collaborate with the robot by inserting specific parameters retrieved during the inspection, which, once elaborated by a decision-making software, like the one shown in [22] for the remanufacturing of some automotive breaks, will give in output if the product is re-manufacturable or not and the steps to follow.

In general, the analysis of the literature pointed out that human–robot cooperation in production systems is becoming the solution also for non-standardized processes, such as inspection and other critical phases of remanufacturing. This facet is witnessed by several scientific contributions, such as in [12, 21, 22].

DSSs and decision-making methods are also used for operations management, such as the scheduling and planning of remanufacturing activities. Fang et al. [23] developed a management framework useful to schedule the operations of the disassembly phase using multi-criteria decision-making methods (MCDM), the Quality Function Deployment (QFD), the Fuzzy Reasoning Petri Nets (FRPN), and a decision making process based on cost driven methods. The decision about the scheduling

of the operations is based on the data acquired through semi-automated processes and optimizing times, costs, and quality of the remanufactured product.

Zheng et al. [24], proposed a methodology based on scenario-based analysis (SBA), using simulation to build different remanufacturing scenarios and making a decision based on a common weighted multi-objective function.

Other MCDMs very used in different aspects of the remanufacturing operations management decision-making are the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP). The last one is used by Vasanthakumar et al. [25] to assess the feasibility of the most critical remanufacturing phase for the specific core, while AHP is used by Fang et al. [23] to build up a new working cycle for the remanufacturing of a core that was not received yet until that date.

Lastly, Charnley et al. [15] used Discrete Event Simulation (DES) and System Dynamics (SD) to define decisions about operations management using as the main variable the quality of the core to be remanufactured that influences the main parameters of the remanufacturing process such as the time and number of operations.

4 Discussion and Conclusions

The bibliometric analysis performed in the first part of the previous section showed the following features:

- Over the years, since 2010, there has been a growing interest of attention from the scientific community regarding the remanufacturing topic and, in particular, the use of DSSs.
- Between the years 2016–2019 the main concerns were of an economic nature and of process optimization. Since mid-2019, there has been an increase in attention to “green” issues such as attention to resources, energy, raw materials, and circular economy.
- The theme investigated is strongly cross-sectorial as evidenced by the origins of the several journals that treat the related issues.

From the SLR analysis, other outcomes can be identified and described. In general, it is possible to say that in the remanufacturing context, the use of decision-making tools is widely spread, and they assist humans in many tasks, such as the operations management or the identification of the returned products' quality during inspection.

Human operators remain essential in the remanufacturing process, as current automated solutions can only provide support and assistance to humans rather than replacing them. Despite significant advancements in AI and other technological innovations, the lack of standardization in remanufacturing processes and the limited information provided by Original Equipment Manufacturers (OEMs) about the products contribute to this reliance on human involvement. Furthermore, even if statistical data are available, it is still not possible to implement standard processes for each fault feature because of their multiple natures, shapes, sizes, and criticalities.

Lastly, it is worth remarking that to enhance the power of the decision-making tools for remanufacturing the information sharing between all the supply chain players will play a fundamental role in improving the efficiency of the remanufacturing operations; this improvement is needed to more strongly integrate the circular economy paradigm in the manufacturing companies, making them ready to accept the next future challenges from the market and sustainability point of view.

The use of decision-making tools is strongly reinforced by the fact that collaborative systems in which humans and robots collaborate are a reality and a need in the remanufacturing context, because of the high level of uncertainty and non-standardized operations depending on the quality of the returned products. This problem is addressed through the use of AI and MCDM, especially during the first steps of the remanufacturing process, i.e. the inspection and disassembly phases.

The use of MCDMs is not only limited to the operative phases of the remanufacturing but is also present in the management of the operative phases, especially in the scheduling and planning activities that are generally identified as the decision-making core for the operations management. The main MCDM methods used in the remanufacturing context are: AHP, ANP, SBA, SD and DES.

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Consumer Acceptance and Preferences Based on Environment Knowledge to Inform Remanufacturing End-of-Life Approach for Electric Vehicle Battery: A Scoping Review Study



Okechukwu Okorie, Yogendra Singh, and Nnaemeka Vincent Emodi

Abstract Product remanufacturing and other End-of-Life (EOL) approaches still remain topical issues in research and policymaking. As observed in the literature, global challenges such as climate change and the subsequent need to reduce greenhouse gas emissions have contributed to driving this interest. While electric and hybrid vehicles are expected to rise in the vehicle market, electric vehicle batteries remain of interest as they typically account for 30–40% of the value of an electric vehicle. While this is a growing concern, the end-of-life use of these products remains a concern. Remanufacturing, which prepares end-of-use products and their components for use through a controlled industrial process, bringing it to “as good as new”. Thus, remanufacturing can be a suggested end-of-life approach for the electric vehicle battery as well as the remanufacturable components in the electric vehicle. While existing studies show consumer knowledge of environmental issues, there are no studies that assess the environmental knowledge of consumers. This scoping review asks the question: from existing research, what are the environmental considerations and end-of-life approaches considered in consumer uptake of electric vehicles? While the broad focus is on electric vehicles, we narrow this interest to electric vehicle batteries for the reasons of component value. A PRISMA scoping review is conducted, and from this, various relevant themes necessary to investigate consumer acceptance and preferences for electric vehicle battery remanufacturing are identified.

O. Okorie (✉)

Department of Engineering, Faculty of Environment, Science and Economy, Streatham Campus,
North Park Road, Exeter EX4 4QF, UK
e-mail: O.S.Okorie@exeter.ac.uk

Y. Singh

Centre for Simulation, Analytics, and Modelling, University of Exeter Business School,
Streatham Court, Exeter EX4 4PU, UK
e-mail: y.singh@exeter.ac.uk

N. V. Emodi

UQ Business School, The University of Queensland, St Lucia, QLD 4072, Australia
e-mail: nnamemka.emodi@utas.edu.au

Keywords End of life approach · Remanufacturing · Electric vehicle · Electric vehicle batteries · Consumer acceptance · Consumer preferences · Environmental knowledge

1 Introduction

Tackling the waste management of electric vehicle batteries remains very important to academics, industry practitioners, and policymakers [1, 2]. With electric vehicles (EVs) registrations reaching very high numbers, for example, China recently reaching approximately 6.9 million in 2022 and consecutively ranking first globally world for 8 years [3], management of the post-manufacturing phase of these EV batteries has become increasingly important in meeting Net Zero targets. Academic researchers consider EVs as effective, sustainable and digitally transformative transportation solutions that support the customer (and the transportation ecosystem) to reduce greenhouse gas emissions and achieve energy efficiency [4, 5].

Aside from China, other countries and regions have introduced policies and legislation that have supported the roll-out of EVs and support to manufacturers. These include the United Kingdom, where the government is implementing mass EV roll-out measures through funding incentives, planning legislation for EVs, and environmental pledges, which are linked to ending the sale of the internal combustion vehicle engines [1]. In the same vein, the European Union has implemented similar EV-supporting policies, such as the European Green Deal [6], which commits to carbon neutrality by 2050, the “Sustainable and Smart Mobility Strategy Package”, which provides an action plan in the form of 14 phased milestones, amongst other policies (within these milestones, five are directly related to EV deployment [7]). Generally, these policies show that the European Union has increased its focus on cutting harmful emissions from passenger cars, light commercial vehicles and low-emissions mobility [8]. Customers and end-of-life approaches remain at the heart of these policies. However, how have consumer preferences and environmental knowledge being able to inform remanufacturing as an end-of-life approach?

At the heart of EVs policies is the EVs batteries. According to estimates from the Global IEA database, 100–120 GWh batteries are expected to be disposed of from automobiles in 2023 [9]. In the context of the waste management and circular economy literature, this waste has various implications. First, due to the make up of these batteries, toxic electrolytes and organic chemicals are expected to pose significant environmental challenges, in addition to human and animal health concerns [3]. In addition, the continued EV deployment has its own attendant challenges of rapid depletion of critical mineral resources, such as cobalt [10]. Finally, depending on the capacity of the battery and the in-use charging efficiency, end-of-life EV batteries are eligible for specific second-life applications such as charging stations [11] as well as circular approaches such as remanufacturing [12, 13].

This study focuses on remanufacturing as an end-of-life approach for electric vehicle batteries. Kamath et al. [12] state that End-of-life (EOL) electric vehicle

(EV) batteries can be remanufactured into second-life batteries (SLBs). Remanufacturing is an industrial process that uses components and parts recovered from used products (called the “core”) for producing new or like-new products [14, 15] and is a key value-retention processes [16], which includes direct reuse, repair and refurbishment. While studies on remanufacturing of EV batteries remain an emerging research area, there is noteworthy literature that suggests that remanufacturing will become a key EOL approach for the batteries in the next few decades. The majority of the study in this area investigates the economic argument for advancing remanufacturing as an option for electric vehicle manufacturing [3, 16]. For instance, Li et al. (2018), utilised Mixed Integer Nonlinear Programming (MINLP) to develop a “cost-effective” closed-loop supply chain model for EV battery remanufacturing. With this model, they show that a 9.81% increase in profit can be achieved when the profit is maximised [17]. Following this, Alfaro-Algaba and Ramirez [45] developed a model for the techno-economic and environmental disassembly of lithium-ion electric vehicle battery, demonstrating the feasibility and effectiveness of the Disassembly Sequence Planning (DSP). In the same year, Xiong [18] evaluated the environmental and economic evaluation of remanufacturing, investigating environmental and economic evaluation of remanufacturing lithium-ion batteries from EVs. They conclude that, the potential cost-saving from battery remanufacturing is approximately \$1.87 kg⁻¹ cell produced [18].

In addition to the End-of-Life approach in electric vehicle studies, a key part of electric vehicle adoption is the perspective of the customers. What are the factors involved in the adoption of EVs by the customer? Several papers examine this perspective. For example, Prieto et al. [46] use of a hedonic price model, shows that “consumers are risk seeking when used car reliability is below the expected reference value and risk-averse when used car reliability is above the expected reference value”. In another customer-based study, Chinen et al. [19] conclude that the customers’ purchasing intention affects the willingness to pay and accept remanufactured batteries by employing structural equation modelling (SEM) on 420 respondents [19]. Finally, Tang et al. [3] apply SEM and agent-based models to show that, “customers perceived behaviour control exerts the highest impacts on recycling intention, followed by economic incentive, subjective norm and self-identity. Following this, we identify an existing gap in the literature: none of the publications investigates the customer’s perspective, acceptance and preferences for remanufactured electric vehicle batteries.

Thus, the aim of this study is to employ a scoping review to investigate consumer perspective, acceptance, and preferences for remanufactured electric vehicles. We ask the following research questions:

- RQ1: What is the state-of-art in the literature on remanufactured electric vehicle batteries from a consumer perspective?
- RQ2: Which theories, context [End-of-Life Approach], characteristics, and methodology are used to explain the purchase behaviour of remanufactured electric vehicle batteries?

- RQ3: What are the gaps in the literature and areas of future research on remanufactured electric vehicle battery acceptance and perception studies?

What drives the choice of consumers when their preferences, consumer acceptance of EVs, knowledge of remanufacturing and the acceptance of remanufactured EVs is put together? Using data from SCOPUS, Google Scholar and Web of Science, we answer the following research questions and make a contribution to the body of work in EV adoption and remanufacturing. The next sections are as follows: Sect. 2, shows the scoping review methodology employed. In Sect. 3 the papers are analysed through the identified themes and finally, we make several relevant conclusions in Sect. 4.

2 Methodology

This study adopts a systematic literature review approach which is in line with the systematic quantitative review literature [20–23]. This review summarises the literature on the technological trends, drivers, and conditions for consumer acceptance of remanufactured electric vehicle batteries. “*Consumer acceptance*” is different from “*consumer preference*”. In simple terms, acceptance measures the level to which a person likes or dislikes a product or service. A preference test is the selection of one product or service over another. The systematic quantitative review was conducted in five stages: (i) define the topic area and identify research question(s); (ii) use keyword search string to identify potential articles for inclusion; (iii) review articles and develop a database; (iv) extract data from the articles and insert into the database; and (v) analyse, refine, and summarise results. Accordingly, the aim of this study is to investigate consumer perspective, acceptance, and preferences for remanufactured electric vehicle batteries. The research questions have been specified in Table 1, which includes the keyword search string used to identify relevant articles from electronic databases. The inclusion criteria listed in Table 1 was used to screen articles included in the final review.

The articles were screened following the PRISMA [24] flow diagram shown in Fig. 1. After screening, 22 articles were included for data extraction and characterisation as presented in Table 1A in Appendix A. The articles were coded through the index number to differentiate literature sources used in the review, and the numbers were placed in square brackets (e.g., [# ‘xy’], where “xy” represents the number allocated to an article in Table XX). The database was structured in a charting table to record information about the author(s); publication year; journal; and country. As a systematic quantitative review, the themes identified in the articles are recorded as “1” in the result section and summarised. The data were subsequently revised and cross-checked by the authors during weekly meetings before finalising the systematic review.

Table 1 The systematic approach for identification and selection of relevant papers

No.	Approach
1	Define the topic area Consumer acceptance and preferences for remanufactured electric vehicle battery
2	Formulate research questions <i>Research aim</i> To investigate consumer perspective, acceptance, and preferences for remanufactured electric vehicle batteries <i>Research questions</i> • RQ1: What is the state-of-art in the literature on remanufactured electric vehicle batteries from a consumer perspective? • RQ2: Which theories, context [End-of-Life Approach], characteristics, and methodology are used to explain the purchase behaviour of remanufactured electric vehicle batteries? • RQ3: What are the gaps in the literature and areas of future research on remanufactured electric vehicle battery acceptance and perception studies?
3	Keyword search string <i>Keyword search term</i> ("consumer" OR "public") AND ("acceptance" OR "preference" OR "knowledge" OR "perception" OR "awareness") AND ("remanufactur*" OR "reprocessed" OR "recycl*") AND ("electric vehicle batter*" OR "ev battery" OR "hybrid electric vehicle batter*" OR "rechargeable energy storage system")
4	Electronic database Scopus and Google Scholar
5	Inclusion criteria <i>Analysis type:</i> quantitative and qualitative <i>Article type:</i> peer-review and grey literature published in English <i>Findings:</i> economic and technology aspect, consumer preferences and awareness, and knowledge gaps <i>Geography:</i> Global scale <i>Period:</i> 2010-present <i>Scale:</i> international <i>Sub-sector coverage:</i> passenger vehicles, taxi, fleet vehicles

3 Findings and Results

As stated in the methodology section (and Fig. 1 and Table 2), we find out that the publications in this area are very recent, with most publications emanating from Asia. Tang et al. [3], argue that China is leading this surge (and the research) due to the wide range of policy initiatives to realise carbon neutrality and address climate change [3]. We also identify that the electric vehicle battery can be recycled, refurbished, reused or remanufactured at its end of life into second-life batteries or SLBs [12]. Table 2 captures the state of the art of the literature. We find out that many consumers are very keen on understanding the EoL of the electric vehicle battery, with studies utilising participant survey data ranking very highly in assessed publications. For instance, Tang et al. [3] sampled 1,083 participants and Li et al. [25] sampled 676 survey participants respectively. The conclusion can be reached that EV consumers are very knowledgeable of EVs and would be engaging in further studies in this area.

Table 2 Identified relevant elements from the included studies (N = 21)

Author(s)	Year	Journal	Funded project/bodies	Focus		Countries examined
				Implemented project or policy	Hypothetical	
[1]	2022	Technology n Society			1	China
[26]	2023	Sustainability (MDPI)			1	Thailand
[27]	2023	Sustainability (MDPI)			1	China
[28]	2023	Topical review	1		1	Global
[29]	2022	Clean Technologies and Environmental Policy		1		China
[30]	2021	International Conference on Big Data and Intelligent Decision Making (BDIDM)	1			China, United Kingdom
[31]	2022	Renewable and Sustainable Energy Reviews	1	1		China
[25]	2023	Journal of Cleaner Production	1	1		China
[32]	2023	Journal of Cleaner Production			1	Malaysia
[33]	2023	Journal of Cleaner Production		1		
[34]	2022	Journal of Cleaner Production	1	1		China

(continued)

Table 2 (continued)

Author(s)	Year	Journal	Funded project/bodies	Focus		Countries examined
				Implemented project or policy	Hypothetical	
[35]	2022	Journal of Cleaner Production	1	1		China
[36]	2022	Journal of Cleaner Production			1	India
[37]	2021	Journal of Cleaner Production	1			Colombia, Finland, Italy, Mexico, Norway, Spain, USA
[38]	2022	Energy	1	1		China
[39]	2020	Energy	1		1	China
[40]	2021	Journal of Manufacturing Systems			1	
[41]	2023	Engineering Applications of Artificial Intelligence	1		1	
[3]	2023	Energy	1		1	China
[42]	2023	Journal of Energy Storage	1		1	Australia, China, Argentina, Chile, the United States, Nevada, Democratic Republic of Congo.
[43]	2022	Transport Policy	1		1	Brazil

(continued)

Table 2 (continued)

Continents examined					Methods used				Type of data			
Asia	North America	South America	Africa	Oceania	Europe	Surveys	Interviews	Case study review	Analytical/empirical	Qualitative	Quantitative	Mixed
									1			1
									1			1
1						1			1		1	
1	1	1	1	1								
		1					1			1		
16	3	3	2	2	3	10	4	2	7	5	7	8
Participant information					Perception of EVs							
Number of respondents	Participants with EVs or intend to buy EVs	Participants from the general population	Rationale	Motivation	Self-efficacy	Individual/community/institution acceptance	Socio-political/market acceptance	Technology acceptance	Safety/risk			
32	1		1	1								
12	1	1	1	1	1		1				1	
335	1	1	1	1								
	1		1	1								
552	1	1	1	1						1		

(continued)

Table 2 (continued)

Participant information			Perception of EVs						Safety/risk
Number of respondents	Participants with EVs or intend to buy EVs	Participants from the general population	Rationale	Motivation	Self-efficacy	Individual/ community/ institution acceptance	Socio-political/ market acceptance	Technology acceptance	
–				1					
405	1		1	1	1	1	1	1	1
676	1		1	1	1				
408		1	1	1	1				
			1	1					
429	1		1	1	1				
567	1	1	1	1	1			1	1
32			1	1					
45	1		1	1					
407	1		1	1	1				
			1	1					
			1	1	1				
1083	1		1	1	1				
			1	1	1				1
31	1		1	1					
	13		19	20	9	1	1	1	2

(continued)

Table 2 (continued)

Perceptions about EVs			Promoting EVadoption				
Sustainability/CE	Innovation	Awareness	Public	Government	Manufacturer	Price	Tech spec
1	1	1	1	1	1		
1	1	1	1	1	1	1	1
1			1		1		
1	1					1	
1	1	1					
1	1	1					
1	1	1					
1	1	1	1	1	1		
1						1	
1							
1				1	1		
1							
1							
1				1	1		
1						1	
1							
1							
1							
1							
1							
1							
1	1	1	1	1	1		
4	17	7	5	6	7	4	1

Generally, we do not find many theories, end-of-life approaches, characteristics, and methodologies used to explain the purchase behaviour of remanufactured electric vehicle batteries as this research area is still emerging. We identify recycling, refurbishment, reuse, and recycling as end-of-life approaches. A number of economic theories and contexts are identified in the papers under review. These include consumer attitudes towards remanufactured electric vehicle batteries, cost theory (consumers will be less willing to buy an expensive remanufactured battery), herd mentality or herd behaviour, government policies which would include incentives for consumers to buy remanufactured EV batteries and green legislation. We also argue that consumer incentives from the remanufacturers are economic theories necessary to understand consumer acceptance of remanufactured electric vehicle batteries. We also identify consumer perception of EV batteries across two phases in the reviewed studies; perception of EVs (this is the perception the consumer has that drives the purchase of EVs), and perception about EVs (this is the perception that the consumer has during the use of EVs). Generally, we conclude that there are multiple drivers that lead the consumer to the purchase of EVs, with sustainability and awareness of EVs contributing to a circular economy being a key contributor to a circular transport economy.

Thus, future studies can explore research gaps which examine the economics and the environmental awareness of consumers' purchase of EVs. This integrated study is identified as a future research area, as consumer awareness and perception of EVs are generally driven by multiple and diverse reasons as captured in Table 2. Multi-disciplinary research exploring economics, environmental, and policy motivation is a research gap that this scoping study readily identifies.

4 Conclusion

The predictions for high sales of EVs for the future will continue as the electric vehicle offers an environment-friendly solution to transportation. While studies show that EV batteries have a lifespan of 10–15 years [44], there is a need to introduce end-of-life approaches such as remanufacturing to the consumer as disposing of EV batteries in landfills is an expensive and environmentally hazardous option [40]. In this scoping review of 21 papers, we attempt to bring some clarity on understanding consumer adoption of EVs should they be aware of the remanufacturing option of the battery. We identify that while EV consumers have a high perception of EVs, they have a low understanding of the batteries and consequent end-of-life approaches. Future studies will need to take this into account, as well as the diverse and complementary motivations of their choice of EVs over internal combustion engine vehicles. An interdisciplinary and integrated approach is suggested for future work.

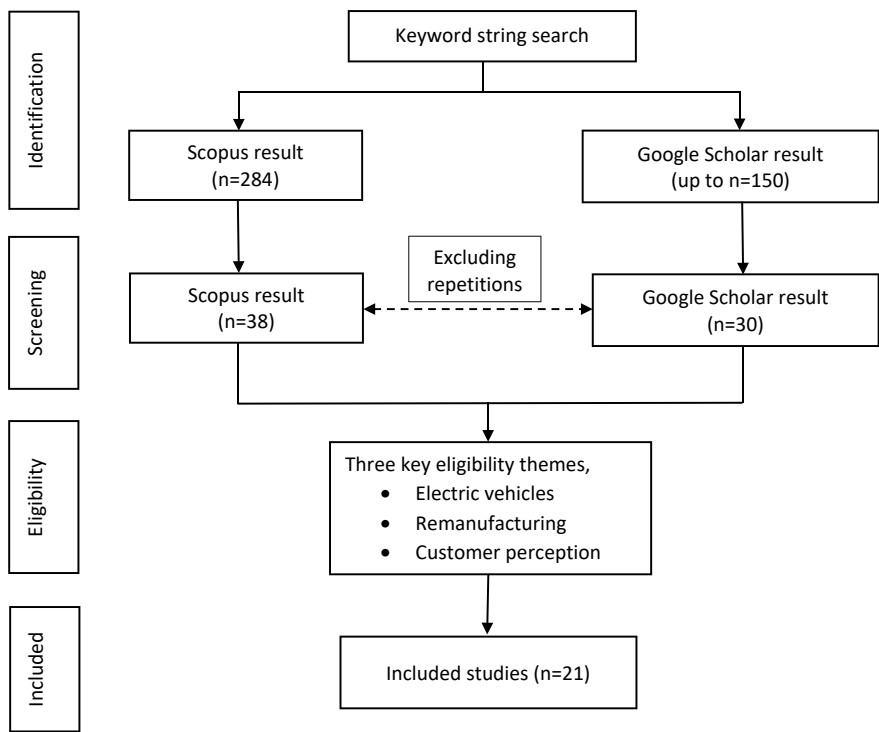


Fig. 1 Diagrammatic representation of keyword string search

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Integration of Augmented Reality and Digital Twins in a Teleoperated Disassembly System



Feifan Zhao and Duc Truong Pham

Abstract Disassembly, a key step in remanufacturing, is almost always performed manually due to uncertainties associated with end-of-life products. In some cases, such as EV battery disassembly, the operator could be exposed to safety hazards. Teleoperation is an effective solution to this safety issue. This paper proposes a teleoperated disassembly system that integrates augmented reality (AR) and digital twin technology. The system establishes bidirectional human-in-the-loop communication between the physical system (the teleoperated robot) and the virtual model. Using AR, the system can provide real-time robot status information to the operator by superimposing a virtual robot on the physical robot and displaying relevant data either in the form of text or a line chart. Furthermore, the proposed approach allows operators to enter the control loop when anomalies are detected, enabling them to receive real-time feedback while remotely controlling the robot. Experiments have demonstrated the effectiveness of the system in monitoring robot status during complex disassembly and offering a more intuitive approach for remotely controlling the robot, thereby improving the safety and efficiency of disassembly operations.

Keywords Disassembly · Teleoperation · Augmented reality · Digital twin

1 Introduction

Remanufacturing restores end-of-life (EoL) products to their initial manufacturing standard [1]. It aims to extend the life of products and their components while reducing waste, conserving resources, and avoiding the environmental impact of manufacturing new products [2]. The remanufacturing process normally includes several steps: disassembly, cleaning, inspection, repair, reassembly and testing [3]. Disassembly is the first and most important operation, as it sets the foundation for the following operations [3]. Due to the high level of uncertainties about EoL products

F. Zhao (✉) · D. T. Pham
University of Birmingham, Birmingham B15 2TT, UK
e-mail: fxz604@student.bham.ac.uk

and the complexity of the disassembly process, it is usually performed manually, resulting in high labour costs and low efficiency [4]. On the other hand, certain disassembly tasks, such as battery disassembly, can pose a significant risk to human operators. They must wear heavy protective clothing to avoid exposure to hazardous materials or potentially dangerous working conditions [5]. The integration of industrial robots and human operators through human–robot collaboration (HRC) has emerged as a new frontier in manufacturing [6]. Human–robot collaborative disassembly, which combines the strengths of both parties, has been introduced to achieve efficient, safe, and flexible disassembly [4].

Teleoperation provides a remote operation solution for human–robot collaboration, enabling humans to work in safer and more comfortable environments even if the robots are exposed to potential harm. This significantly improves personnel safety, task efficiency and flexibility in dangerous disassembly tasks. There is a large body of literature on robot teleoperation in which various approaches have been adopted to accomplish effective and efficient remote robot control, such as gesture and voice control, software interfaces, haptic feedback controllers, and EMG-based techniques [7]. However, due to the complexity of disassembly tasks, there are challenges when deploying these methods on teleoperated disassembly, especially for inexperienced users. A notable challenge is the absence of an intuitive and easy-to-use interface for remotely controlling industrial robots to improve the performance of human operators [8].

Augmented reality (AR) is considered a more natural human–robot interaction technology because it seamlessly integrates digital information into the user's real-world environment [9]. By overlaying virtual elements, such as 3D models, annotations, or instructions, onto the physical space, AR enhances the user's perception and understanding of the task at hand [10]. The implementation of AR technology creates a new design space and an opportunity to enhance the naturalness of human–robot interaction in robot teleoperation. Li et al. [11] proposed an AR-assisted multi-robot collaborative manufacturing system. Within this system, during the critical phase of motion planning, conventional kinematics-based robot movement was replaced with a reinforcement learning algorithm. Lin et al. [12] described an AR-teleoperated system that could present the reconstructed 3D scene of the remote area at the local station interactively. This immersive experience reduces cognitive load, shortens the learning curve, and fosters a more efficient and collaborative workflow between humans and robots [13]. While most research efforts focus on the utilisation of AR technology for robot control, real-time system feedback and display during the control process have not been studied in depth.

Digital Twinning is a technology paradigm that bridges the physical and virtual worlds by creating a digital replica or 'twin' of a physical asset [14]. This replica includes not only the geometric and material properties of the asset but also its operational processes and behaviours for tasks such as real-time monitoring, predictive analysis, and problem diagnostics [15]. A Digital Twin (DT) helps engineers to understand and predict the behaviours of complex systems, enabling better design, operation, and maintenance decisions. More importantly, a DT can dynamically update its model via real-time data feedback, reflecting the status and performance

of the physical asset [14]. Both AR and DT are powerful tools fostering the fusion of the virtual and physical worlds. Given that a DT is model-based and requires real-time interactive control, it is natural to integrate AR into a DT system. This paper proposes a teleoperated disassembly system that integrates AR and DT, as shown in Fig. 1. An AR environment is created that provides an intuitive display of system status information and an operational interface by overlaying virtual information and operational elements on the physical environment. Meanwhile, the DT provides an accurate model and real-time data, ensuring the accuracy and timeliness of the AR interface. In this way, bidirectional human-in-the-loop communication between the physical system and virtual model is possible, which enables operators to understand and interact with remote robots intuitively through the AR interface, accomplishing complex disassembly tasks efficiently and safely.

The use of AR and DT provides two-way communication between the human operator and the disassembly system. The AR interface enables efficient interactions with remotely located robots and the performance of complex disassembly tasks. While many studies focus mainly on the use of AR, our research emphasises the importance of real-time feedback during control, which effectively addresses the challenges of disassembly and positions our system as a solution for smart remanufacturing.

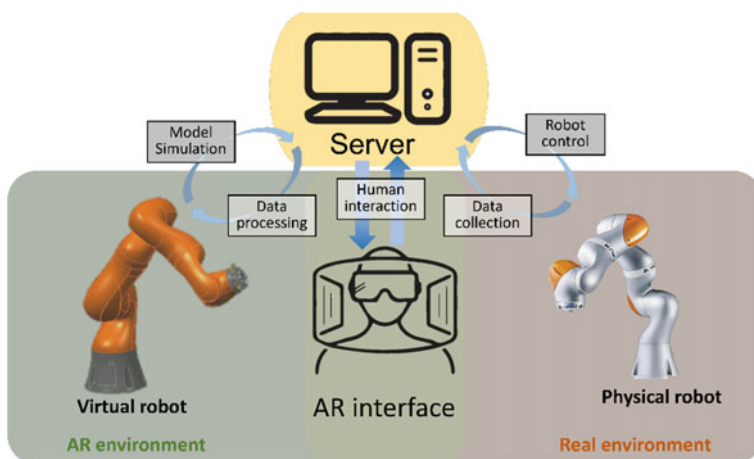


Fig. 1 Overview of the system

2 System Design and Implementation

2.1 *System Framework and Hardware/Software Infrastructure*

The teleoperated disassembly system with integrated AR and DT, as presented in this paper, aims to enhance the user's ability to intuitively monitor tasks and remotely control the robot. The development of this system focuses on two aspects. First, the system collects and processes data from the robot's sensors while the robot is performing the disassembly task. These data are displayed on the AR interface in real time, providing the operator with a better and more detailed understanding of the task progression and the status of the robot. Second, the system uses AR technology to create an interactive AR scene by superimposing holograms onto the physical workspace. In the system, a virtual robot is superimposed on the physical robot, allowing the operator to control the physical robot by directly interacting with the virtual robot. This approach not only improves user engagement but also provides a seamless and intuitive interface for users to transmit their commands to the robot.

Figure 2 illustrates the framework of the proposed system. It consists of three main components: an AR head-mounted display (HMD), a robot control computer and a physical robot. In this system, the HMD presents a virtual robot superimposed onto the physical robot, immersing the operator in an intuitive AR environment. This not only creates an AR scene but also provides a direct and intuitive interaction method for the operator, enabling them to guide the physical robot with gesture control. The robot control computer serves as the brain of the operation. It processes the commands sent by the operator, performs essential motion planning and conducts inverse kinematics. To achieve these functionalities, the robot operating system (ROS) is utilised, providing a flexible and robust framework for robot software development. In this case, ROS acts as an intermediary to translate high-level operator's commands into robot movement. The communication library, ROSBridge, facilitates data transmission between the HMD and the robot control computer. It establishes a seamless wireless connection and manages the necessary translation between different data formats. This efficient communication protocol ensures real-time interaction and control. Two-way communication between the physical robot and the robot control computer is achieved via the Sunrise Bridge component of the *iiva_stack*, a software stack specifically designed for KUKA LBR *iiva* robots. This crucial link permits the transmission of motion planning results to the physical robot. In addition to transmitting commands, the Sunrise Bridge also allows the robot control computer to retrieve vital information from the robot, ensuring a continuous exchange of data. Therefore, as the robot executes tasks, sensors installed on the physical robot collect data, such as the joint states of the robot. This collected information is relayed to the robot control computer for further processing. The processed data are then displayed to the operator via the HMD. This real-time feedback mechanism allows the operator to be fully aware of the robot's status and task execution, thus improving the system's transparency and trustworthiness.

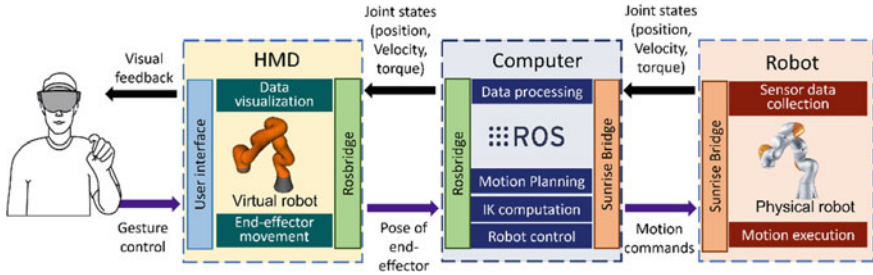


Fig. 2 System framework

Figure 3 illustrates the workflow of the entire system. First, the robot performs the disassembly task according to a predefined programme. In addition, the system can continuously collect data from the robot’s sensors. These processed data are then converted into a visual format and projected onto the operator’s AR HMD. This gives the operator a comprehensive, real-time view of the robot’s status and the progress of the task being performed. The operator can intervene by entering the control loop if an abnormal situation is detected. Through the AR interface, the operator can control the physical robot by manipulating the end-effector of the virtual robot. This iterative process continues until the disassembly task is completed. This mode of operation ensures effective synergy between automated processes and human supervision, optimising the efficiency of the disassembly task, facilitating real-time control and increasing the transparency of the system.

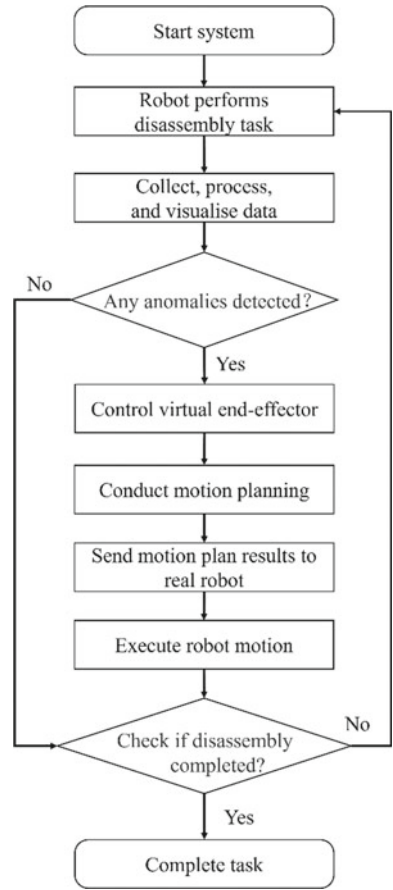
2.2 Real-Time Data Acquisition, Processing, and Visualisation

In the system, the robot’s status information is first collected, processed, and presented in the AR environment, providing the operator with a comprehensive understanding of the robot’s condition and task progress, as illustrated in Fig. 4.

Thanks to the sensors located on each joint of the KUKA iiwa 14 R820 robot, the system can subscribe to the raw data collected by these sensors. These data are then sent to the robot control computer for processing via a series of nodes designed within the ROS environment, achieving seamless integration with the Java-based ecosystem of the KUKA Sunrise controller.

A key part of this process is the real-time updating of the robot’s joint position. When the physical robot moves, the ROS processes the joint position information, updates the corresponding positions of the virtual robot, and reflects these changes in the AR environment. As a result, the twin moves almost synchronously with the physical robot, providing an immediate and intuitive visual representation of the robot’s status and task progress.

Fig. 3 Workflow of the system



In addition, a detailed display of robot joint information plays a significant role in helping the operator understand the robot's status and task progress. Therefore, the data processing procedure also involves extracting useful key information from the raw data, including joint name, position, velocity, and torque. Then, a data format conversion is performed since the robot joint sensor data from ROS-specific message types (such as `sensor_msgs/JointState`) must be translated into a JSON format suitable for AR HMD display. Once processed, the data are finally transmitted to the HMD device, where they are presented to the operator in two different ways. As shown in Fig. 5, first, numeric data of each joint's state are converted into a text form, directly displayed next to the corresponding virtual robot joint, allowing the operator accurately to perceive the current state of the robot. Second, robot joint torque data are used to draw line charts. Joint torque can accurately reflect the force condition of the robot, which is essential for the operator to assess task execution. For instance, during a disassembly task, if joint torque abruptly increases, it may indicate that the robot is trying to move a component that is unexpectedly stuck or that the robot

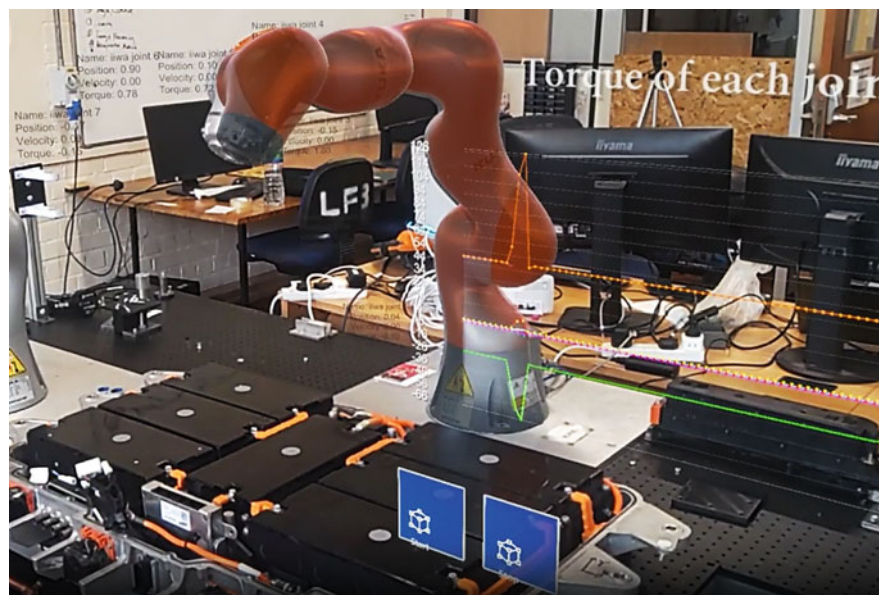


Fig. 4 Display robot status information in the AR environment

is exerting too much force on a component, which could lead to damage. In such cases, real-time monitoring of joint torque and its display as a line chart can assist the operator in quickly identifying potential issues and taking necessary corrective measures. Therefore, a line chart was designed for torque in the AR environment, with different colours representing different joint torques. Two buttons are added beneath the line chart to control the start and stop of the line chart drawing.

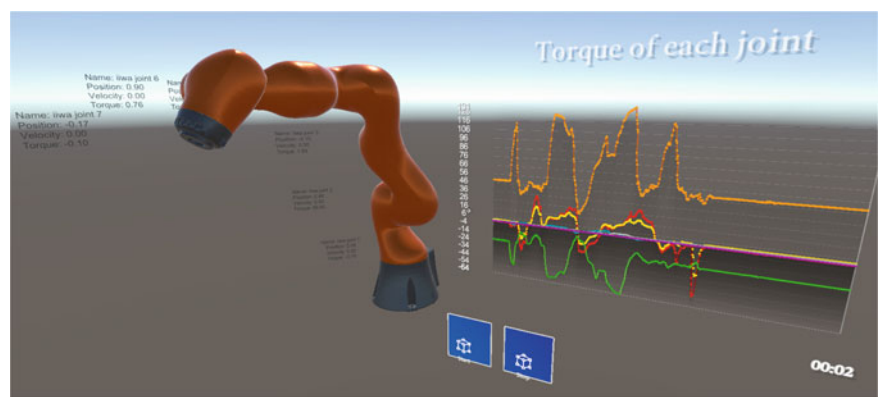


Fig. 5 Display robot status information in two different ways

These two methods of information display enhance the operator's understanding of the robot's status and task progress, enabling more accurate decision-making. This design makes full use of the advantages of AR technology, realises the visualisation of information, and conveys complex robot data in a user-friendly manner, strengthening the efficiency and accuracy of human–robot interaction.

2.3 AR Robotic Control

To truly realise DT, it is vital to establish bidirectional human-in-the-loop communication between the physical system and its virtual model. This setup enables the operator to intervene and control the robot in response to any anomalies in the control loop. After achieving the virtual model updates according to the physical system and realising the display of robot joint information, the goal is now to control the physical robot by manipulating the twin. The AR interface is described in Fig. 6. With the Vuforia Engine and its image marker, accurate alignment of the virtual and physical robots is achieved, ensuring seamless integration.

Operators interact with the virtual robot through a gesture-based system, making selections and manipulating the end-effector of the virtual robot. The user experience is akin to manipulating an object in the physical world, with the virtual robot serving as an intermediary for interaction with the physical robot. For instance, in Fig. 6, the operator indicates their selection of the virtual end-effector by pointing at it with a ray from their index finger. Upon closing their thumb and index finger, akin to a pinch gesture, the virtual end-effector is selected. Subsequently, the movement of the operator's hand guides the selected virtual end-effector to the desired position. This interaction is tracked in real time, with the positional data of the virtual end-effector sent to the robot control computer.

Upon receiving the end-effector's positional data, the MoveIt! Framework [16], which has an integrated inverse kinematics solver provided by the Kinematics and Dynamics Library (KDL) [17], is activated. This solver generates joint configurations allowing the robot to reach the user-indicated position. Out of the generated joint configurations, the one that is most similar to the robot's current pose is selected. The joint angles corresponding to this optimal configuration are computed and promptly applied to both the virtual and physical robots. This mechanism ensures congruity between the virtual and physical robots' actions, thereby creating a more immersive and intuitive control experience for the operator. The trajectory planning phase for the robot leverages the capabilities of the Open Motion Planning Library (OMPL) [18] integrated within the MoveIt! Framework. OMPL provides a wide array of sampling-based motion planning algorithms, supporting an efficient search through the robot's state space for valid trajectories that align with the operator's inputs. This remote control method is particularly beneficial when the operator identifies anomalies through AR monitoring and needs to intervene promptly in the control loop to direct the robot's actions remotely.

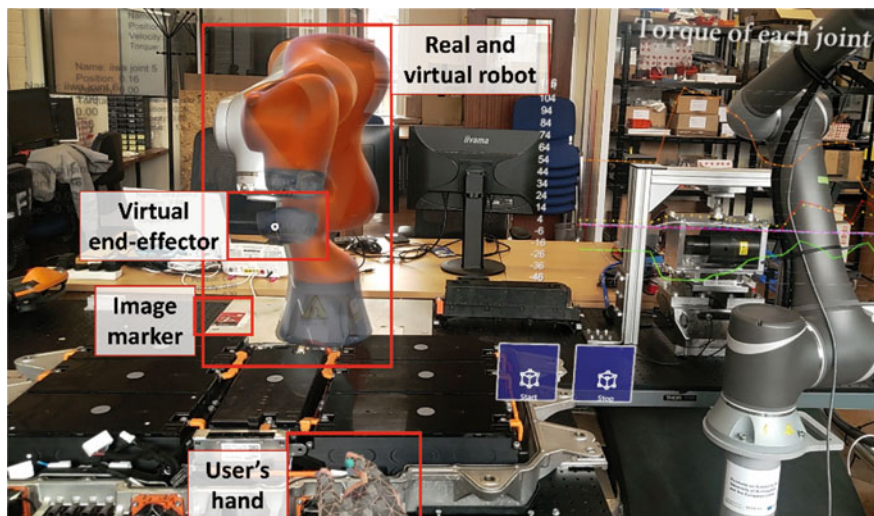


Fig. 6 AR robot control interface

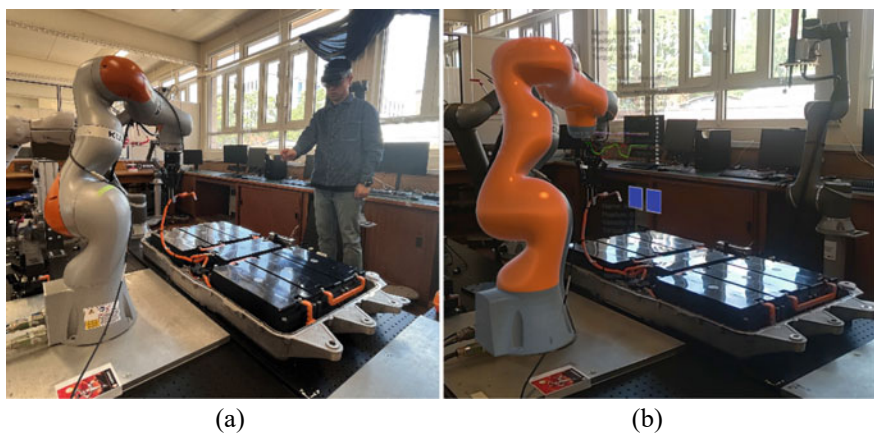


Fig. 7 Layout of the human–robot collaborative disassembly workstation. **a** Physical scene **b** Cyber scene

3 Experiments and Discussion

3.1 Experimental Setup

The proposed system was deployed on a human–robot collaborative disassembly workstation. Figure 7 shows the layout of the workstation and the equipment used, which includes the KUKA LBR iiwa 14 R820 robot [19] and the Robot-iq 2F-85

gripper. In addition, the operator wore the AR headset and Microsoft HoloLens AR glasses [20] and monitored and interacted with the robot from a safe distance. The developed AR robot control interface runs on an external PC workstation with an Intel Core i7-11800H CPU (at 2.30 GHz), 32 GB of RAM and an Nvidia GTX 3070 8 GB GPU. The workstation used Microsoft Windows 10 as the operating system and Visual Studio 2019 as the integrated development environment. Unity LTS version 2020.1.10f1 was used in combination with tools such as MixedReality Toolkit Unity to build the AR interface. To connect the AR environment to the physical robot control system, the ROS framework [21] was used on another PC running Ubuntu 20.04. This framework provided a flexible and stable environment for developing robot software. A WiFi router functioned as the communication hub, establishing wireless connections between all devices, while the robot maintained reliable data transmission through a wired connection. The usability of the system was verified by removing cables from an EoL EV battery.

3.2 *Demonstration*

During the cable removal task, the robot often encounters unforeseen situations, such as the cable getting stuck in the battery pack. If the robot continues to follow the preprogramming under these circumstances, applying force could lead to potential damage to both the cable and the robot. The system addressed this problem by providing the operator with real-time insights into the changing torque trends of the robot, as well as displaying specific torque values at each joint in the AR environment, as shown in Fig. 8. This information allowed the operator to quickly detect anomalies and intervene manually in the control loop. The intervention took the form of gesture-based remote control of the robot, facilitated by the AR interface. During this manual control phase, the operator was able to continuously monitor the real-time force status at each of the robot's joints via the AR display. This ensures that the task can be completed safely and efficiently, even in the presence of unexpected issues.

3.3 *Discussion*

This paper has presented a teleoperated disassembly system integrating AR and DT. The system will be useful for manufacturing and remanufacturing applications where proximity to human operators is not advisable, such as the assembly and disassembly of hazardous (for example, explosive, radioactive or extremely hot) products. While the information acquisition in this system mainly relies on sensors installed in the joints of the KUKA iiwa robot, the flexibility of its design allows access to different robot platforms and collection of diverse state information.



Fig. 8 Demonstrative case: cable removal task

The AR robot control method described in this study is based on the “hand rays” feature provided by HoloLens, which allows the operator to interact with the hologram from a distance. This interaction method has certain distance limitations. The experiments conducted showed that “hand rays” are suitable for interaction up to a range of 5 m, but as the distance increases, the interaction accuracy declines. Therefore, to achieve remote operation that is not distance-limited, one could consider collecting workspace information through sensors such as cameras and solving the distance problem by reconstructing the workspace scene at the remote side. Additionally, the precision of positioning in the AR environment remains a challenge, necessitating further research into methods to enhance the accuracy of AR registration and tracking.

4 Conclusion

This paper has introduced an innovative system that realises bidirectional human-in-the-loop communication between a physical system and its virtual model. Utilising AR technology, the system conveys real-time robot task information and status to the operator, providing both comprehensive system status updates and an intuitive method for robot operation. More importantly, this approach allows the operator to intervene in the control loop and receive immediate feedback while remotely controlling the robot to complete disassembly tasks when abnormal situations arise, significantly enhancing task safety and efficiency. Furthermore, the system’s function has been demonstrated through an application case involving the removal of a cable from an EoL EV battery. This successful application highlights the great potential

of the proposed system, showing its adaptability and utility in a variety of complex and hazardous task scenarios.

Future work will use AR technology to develop more diverse and vivid interfaces for the real-time presentation of more complex information as the robot executes tasks. Furthermore, more than just sending commands to the robot is expected when human intervention is required in the control loop. For example, it is planned to enable robots to learn and mimic human problem-solving strategies. Such learning capabilities of robots can improve their autonomy and intelligence, opening new possibilities for human–robot collaboration.

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Game Theoretic Model Based Human–Robot Collaboration in Waste MP (Multi-peripheral Imaging) Device Disassembly for Remanufacturing



Anjan Choudhury, Ankita Ray, and Amit karmakar

Abstract Disassembly is a significant step in remanufacturing of acquired End-of-Life (EOL) multi peripheral (MP) imaging device. Most of the cases disassembly processes are done manually, which is very exhaustive and has low disassembly efficiency. Recently, robotic disassembly sequence planning (DSP) has widely been studied. It is mainly designed to improve disassembly efficiency and to minimize disassembly cost and time before executing the disassembly process. Further, Human–Robot collaboration (HRC) has gained considerable attention to handle difficulties in DSP in remanufacturing. Therefore, in this paper, DSP of EOL of MP device for Human–robot collaboration is developed by the Stackelberg game theoretic model. This game-theoretic model can be able to manage the volatile and uncertain features of human operators to obtain human-oriented HRC disassembly. In this work, firstly, the Stackelberg model is developed to generate feasible disassembly sequences of EOL of MP device. Further we have presented comparison between game theory and non-game theory based HRC approach.

Keywords Human–robot collaborative disassembly · Stackelberg model · Game theory · EOL products

A. Choudhury (✉) · A. Ray

Robotics and Additive Manufacturing Technology Department, Maulana Abul Kalam Azad University of Technology, Kolkata, WB, India
e-mail: anjan.choudhury@makautwb.ac.in

A. karmakar

Industrial Engineering and Management Department, Maulana Abul Kalam Azad University of Technology, Kolkata, WB, India

1 Introduction

1.1 Background and Motivation

The significant strategy of circular economy is remanufacturing [6]. Remanufacturing process consists of several stages, among them important step is used product disassembly [3]. Disassembly is an important process in remanufacturing to recover valuable metals and components from End -of-life (EOL) items. In recent practice, most of the disassembly processes are obtained manually which is more labour intensive as well as cost effective [2, 3]. However, due to several drawbacks of manual disassembly, recently manufacturing industries focuses on applying intelligent technologies to implement automatic or semi-automatic disassembly procedures [8]. In current practice, human–robot collaboration (HRC) has gained attention of manufacturing industries. Many applications of HRC disassembly system can be found in recent literatures such as the LBR iiwa range from KUKA [7], the YuMi from ABB [1] are generally known as cobot and these cobots directly interact with human operators to perform disassembly operation [5]. *Therefore, motivated from the above scenario, in this study we aimed to develop a HRC disassembly system to disassemble EOL multi peripheral device.*

1.2 Product Evaluation and Problem Statement

Print and imaging equipment have several impacts on environment from manufacturing to disposal. These comprise virgin material consumption, energy consumption and waste generation during disposal. However, due to proactive environmental legislation such as the WEEE, the print industry focused on adaptation of sustainability principles. Therefore, as a result print industries embrace remanufacturing decision in order to save raw material and energy consumption. Further, imaging devices such as printers and MFPs (Multifunction Peripherals) are identified as suitable products for remanufacturing as valuable and complex components can be retrieved at the end of their first life (<https://quocirca.com/content/remanufacturing-in-the-print-industry/>). It can be found that several print industries such as Canon, Ricoh, Lexmark, Xerox successfully practice remanufacturing activities (<https://www.ricoh-usa.com/en/products/greenline>; <https://www.canon-europe.com/business/products/office-printers/multifunction/black-and-white/imagerunner-advance-eq80-6275i/>; <https://www.xerox.com/en-us/about/corporate-social-responsibility>; <https://csr.lexmark.com/circular-economy.php>). Disassembly is a complex and essential step in any remanufacturing activity. *Hence in this study, we focused on multi-peripheral printing device disassembly and it is shown in Fig. 1.*

Disassembly of Multi-peripheral (MP) imaging device is a complex process. From the existing literature it can be found that disassembly by human and robot

Fig. 1 End of use multi-peripheral imaging device



collaboration is quite new concept which can improve disassembly time and disassembly complexities. Therefore, in our study we adopt human–robot collaborative (*HRC*) system for disassembling multi-peripheral print and imaging device in order to improve disassembly process. In the subsequent section, we presented economical and methodical feasibility of *HRC* resources and then disassembly resource identification has been obtained.

1.3 Contribution of the Study

Game-theoretic application in human–robot collaborative system is a new concept and discussed by several researchers. Disassembly sequence planning by game theoretic approach was discussed in recent literature [12]. These authors presented the comparative analysis of game theoretic and non-game theoretic approach and highlighted benefits of applying game theory in *HRC* based disassembly sequence planning. Therefore, in our study we used the same methodology to present *HRC* based disassembly sequence planning of multi-Peripheral device disassembly. In our research, we tried to find the answer of the following research question:

- (i) *Does game theoretic approach provide better solution than non-game theoretic approach while disassembling MP device?*

However, we found case study-based articles, where authors proposed a method to disassemble and to validate the method, they took an EOL product disassembly case

as an example. In this study, we took an EOL multi-peripheral device to disassemble and choose a previously proposed methodology to examine how effectively we can implement in order to get better solution. Further, we classified the entire MP device into various modules and module wise disassemble tasks has been determined. Moreover, we assigned module-wise disassemble tasks to disassemble resources. Finally, we applied Stackelberg game theory to obtain the disassemble sequence for HRC system.

1.4 Related Literatures and Research Gap

Parsa et al. [11] introduced an HRC-based disassembly planning technique for EOL products. Further, genetic algorithm was used to find the best disassembly sequence based on disassembly efficiency and cost. Authors mentioned that, jobs those are very sophisticated and highly flexible could be allocated to humans, and repetitive jobs could be assigned to robots. Several examples of application can be found in literature such as, Huang et al. [5] designed a cobot to disassemble press-fitted components coming from automobile water pumps. Again, Huang et al. [5] demonstrated a robotic disassembly cell consisting of two cobots and a human operator. Recently, consisting of two cobots and a human operator. Recently, Zhou et al. [12] presented game theoretic based HRC disassembly for removing screws from EOL products. Game theory for HR collaboration can be found in research work of Gabler et al. [3] and Nikolaidis et al. [10].

From the above back drop, we found various application of HRC disassembly of EOL products. However, past articles [4, 11, 12] presented the application of game theory based HRC considering a simple EOL product. Application of the game theory based HRC in complex EOL product has been overlooked by those previous authors. Therefore, by considering this research limitation we used game theory based HRC disassembly approach to disassemble EOL Multi peripheral imaging device. Hence, we presented the application of game theory based HRC disassembly approach in comparatively complex EOL products to describe the usefulness of this approach. In the next section we provided methodology for this research study.

2 Methodology

2.1 General Steps for HRC Disassembly

In the first step of Fig. 2, we identified disassembly requirements by product evaluation and then economical and methodical feasibility is obtained considering disassembly resources such as human operator and collaborative robot. The disassembly process includes the delineated disassembly jobs and operations. Later, appropriate

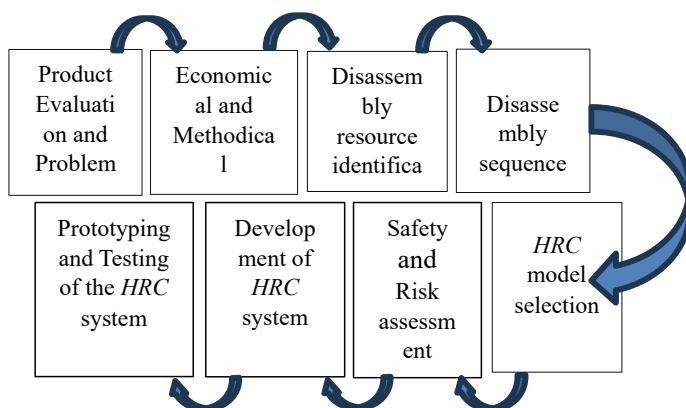


Fig. 2 General Steps for *Human–Robot Collaboration* for disassembly process

disassembly sequences and collaborative models are determined. Afterwards, disassembly jobs are allocated to human operators and the robot. Safety and risk assessment of *HRC* for printer disassembly are carried out. Finally, the *HRC system* is prototyped and tested.

2.2 *Disassembly Resource Identification (Robotic Arm)*

A robotic arm is a mechanical device that imitates the motions and dexterity of a human arm. It consists of a series of joints and segments that allow for flexibility and motion. These arms are widely employed in various sectors for jobs requiring precision, strength, and repeatability. A robotic arm excels at doing repeated operations with excellent accuracy when unscrewing components. The robotic arm, outfitted with specialised end-effectors such as grippers or wrenches, can safely grab and move things. The arm's joints let it reach numerous angles and orientations, allowing it to access confined locations and remove components from varied angles. It is presented in Fig. 3.

2.3 *Disassembly Sequence Designing and Disassembly Job Allocation*

To demonstrate the applicability of Human–Robot collaborative model, we considered End-of-Use multi-peripheral imaging device (*it is a sophisticated device consisting 160 parts*) as an example. First of all, we divided the multi-peripheral

Fig. 3 Robotic arm for disassembling screws from MP device

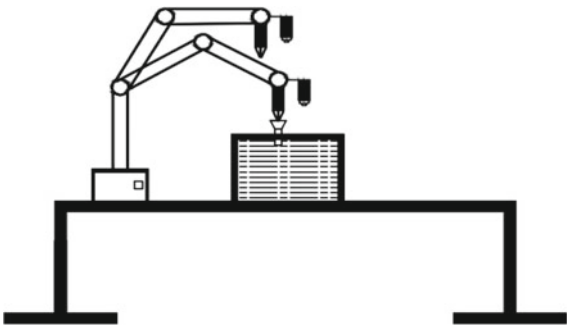


Table 1 The modules of the multi-peripheral imaging device

End-of-use product	Module no.	Description	Module no.	Description
 Multi-peripheral (MP) imaging device	Module 1	Exterior of MP device	Module 12	Fusing unit
	Module 2	Operation panel	Module 13	Paper exit section
	Module 3	Optics sections of MP device	Module 14	Duplex units
	Module 4	Laser unit	Module 15	Driver section
	Module 5	Bypass feed section	Module 16	Electrical sections
	Module 6	Paper cassette	Module 17	Frame sections
	Module 7	Paper registration unit	Module 18	DDST unit
	Module 8	Paper feed sections	Module 19	BICU boards
	Module 9	Vertical transport		
	Module 10	PCUs		
	Module 11	Toner supply unit		

imaging device into different modules (given in Table 1) and then disassembly sequence for the modules have been obtained.

However, some unfastening jobs where flexibility is required, those are assigned to human operators. As an example, we consider only module 1 to disassemble by using game theory based HRC approach. Hence, in Table 2, we presented the disassembly job allocation to resources.

3 Methodology of HRC Disassembly of MP Device

In this study, Stackelberg game theory-based methodology for HRC model development has been considered from Zhou et al. [12]. In this HRC model, human operator who has capability to handle uncertainties is considered as leader and robot is considered as follower (Fig. 4).

Table 2 Disassembly jobs for Module 1 are allocated to Human operator and Robot

Module no.	Jobs	Job code	Human operator	Robot
Module 1 (exterior of MP device)	Unfastening 3 (M3 × 8) Tapping Screws to open Left cover	J1	–	✓
	Pick up and separate left cover	J2	✓	–
	Unfastening 2 (M3 × 8) tapping screws to open left scanner cover	J3	–	✓
	Separate left scanner cover	J4	✓	–
	Unfastening 2 (M3 × 8) tapping screws to open exit cover	J5	–	✓
	Separate Exit Cover	J6	✓	–
	Unfastening 1 (M3 × 8) tapping screws to open rear scanner cover	J7	–	✓
	Separate rear scanner cover	J8	✓	–
	Unfastening 7 (M3 × 8) tapping screws to open rear cover along with application cap, IC card cap and paper bank cap	J9	–	✓
	Separate rear cover, application cap, IC card cap and paper bank cap	J10	✓	–
	Unfastening 3 (M3 × 8) tapping screws to open right scanner cover, right rear cover	J11	–	✓
	Separate right scanner and right rear cover	J12	✓	–
	Unfastening 3 (M3 × 8) tapping screws to open front cover along with cover magnet and magnet catch	J13	–	✓
	Separate the model name plate and operation instruction plate	J14	✓	–
	Unfasten 2 bolts from rear cover	J15	✓	–
	Unfasten 3 (M3 × 8) tapping screws to open left upper cover, exit rear cover	J16	–	✓
	Unfasten 1 (M3 × 8) tapping screws to open energy decal part	J17	–	✓
	Separate main switch cover and panel logo	J18	✓	–

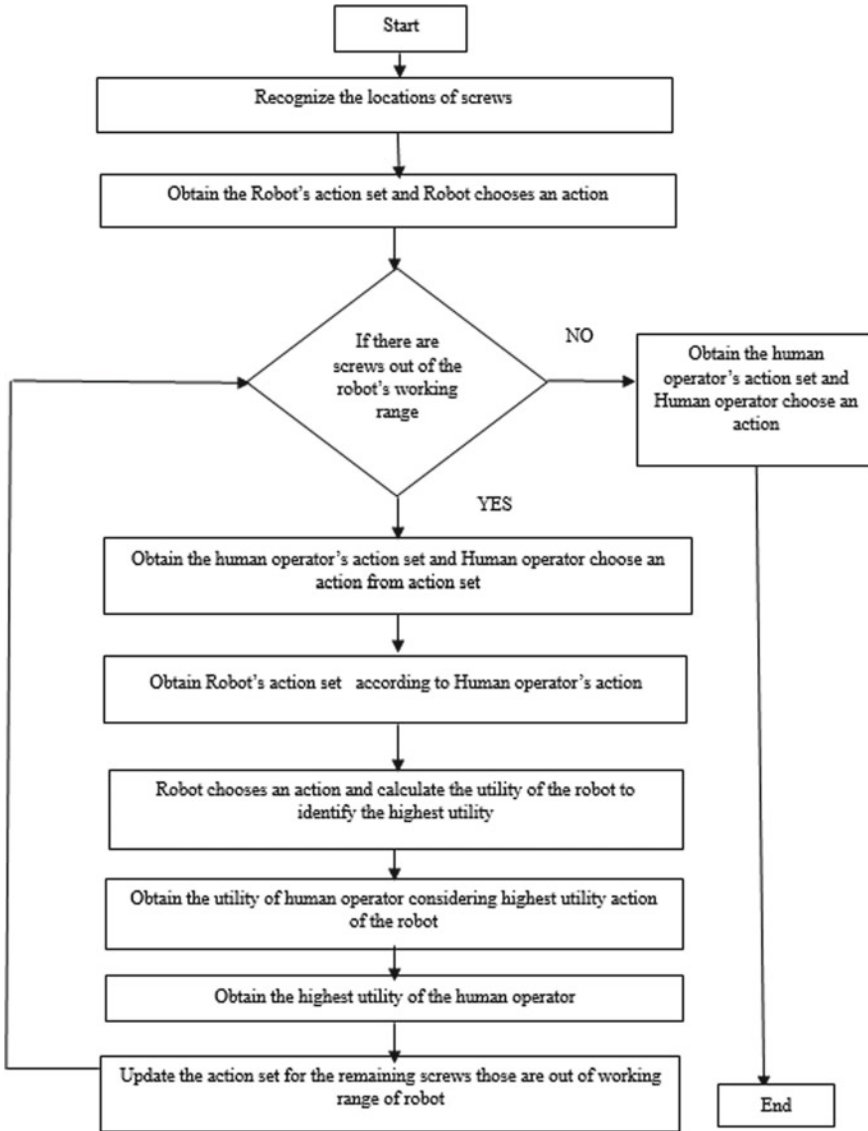


Fig. 4 Flowchart of Stackelberg model for HRC- based disassembly

In this study, we only considered that robot will disassemble the screws. Therefore, like Zhou et al. [12] the utility of the human operator has been assumed to be dependent on two factors: distance between human operator and robot and disassemble efficiency. The utility of robot depends on two factors: safety feeling of human operator and disassembly efficiency. The utility of robot's depending on safe distance is

like the human operator’s utility. Disassembly efficiency is obtained by the required moving distance of the robot for removing screw.

3.1 Evaluation Criteria for HRC Based Disassembly

In this study, we considered two evaluation criteria for HRC based disassembly of MP device and these criteria are discussed in below: Total Disassembly time (D_T): D_T is the total disassembly time for disassembling entire Multi-peripheral device by HRC system. Smaller D_T means high disassembly efficiency. The safety index (S_I): In HRC based disassembly process, it is required to maintain safe distance between human operator and robot.

4 Results and Discussions

In this section we presented the applicability of the above-mentioned methodology in case of MP device disassembly. We have selected one module (Module 1) among 20 modules to demonstrate the applicability of Stackelberg Game theory based HRC disassembly. Further, we provided total disassembly time and safety index values for each module and presented the comparison between game theoretic disassembly and non-game theoretic disassembly of End-of-life MP device. The parameters in this disassembly process have been given in Table 3.

Table 3 Parameters of disassembly process of MP device

Parameters	Estimated time (Avg.)	Estimation process
The speed of the robot of disassembling normal screw	3.8 s	Experimental
The speed of the human operator of disassembling normal screw	7.5 s	Experimental
The speed of the human operator to separate components from main body parts	5 s	Experimental
The speed of the human operator to pick up the components and keep aside	6 s	Experimental
Moving speed of the hand of the human operator for disassembly	10 cm/s	Literature
Moving speed of the arm of the robot for disassembly	8 cm/s	Experimental
Safe range I of the human operator	15 cm	Literature
Safe range II of the human operator	25 cm	Literature

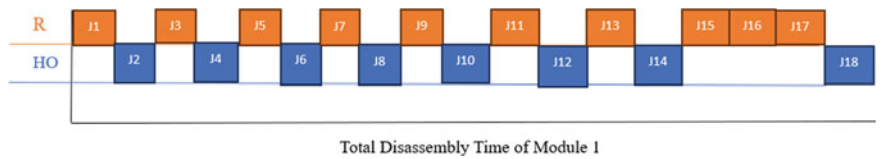


Fig. 5 Disassembly job sequence of Module 1 in normal condition

4.1 Game Theoretic Disassembly

Disassembly of Module 1 consists of 18 disassembly jobs. In the normal condition, while all screws are within range of robot then job sequence can be represented as Fig. 5.

In normal scenario while all screws are within range of robot, then the disassembly process will start from robotic operation with unfastening screws. We have estimated utilities of human operator and robot choosing different actions from the action set during J1 to J18. After that, we estimated total utilities for each disassembly resources by considering equal weightage of the safety and efficiency utility. Finally, we estimated total disassembly time and safety index and it is given in Table 4.

In case of normal scenario while all screws are removed by robot, total disassembly time to disassemble Module 1 is estimated 222.5 s. or 3.7 min by following Stackelberg model. In the subsequent paragraph we presented the scenario while are screws are not be removed by robot and human operator will assist robot to remove the screws. In this scenario, suppose J3, J7, J11 and J16 disassembly of screws are performed by human operator. Thus, the disassembly task sequence has been given in Fig. 6. Now we have estimated total disassembly time and safety index for above scenario and it is given in Table 5.

Table 4 Total disassembly time and safety index during each disassembly activity of Module 1 in normal condition

Disassembly Jobs	Total disassembly time (s)	Safety index	Disassembly job	Total disassembly time (s)	Safety index
J1	11.4	0.64	J10	30	0.41
J2	15	0.51	J11	11.4	0.64
J3	7.6	0.47	J12	15	0.40
J4	7.5	0.43	J13	11.4	0.39
J5	7.6	0.49	J14	15	0.60
J6	7.5	0.46	J15	15	0.46
J7	3.8	0.61	J16	11.4	0.67
J8	7.5	0.43	J17	3.8	0.33
J9	26.6	0.49	J18	15	0.62

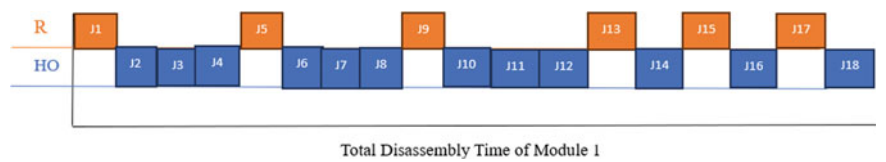


Fig. 6 Disassembly job sequence of Module 1 while human operator assist robot to remove screws

Table 5 Total disassembly time and safety index during each disassembly activity of Module 1 when all screws are not removed by robot

Disassembly jobs	Total disassembly time (s)	Safety index	Disassembly job	Total disassembly time	Safety index
J1	11.4	0.61	J10	30	0.41
J2	15	0.41	J11	22.5	0.67
J3	15	0.64	J12	15	0.41
J4	7.5	0.43	J13	11.4	0.44
J5	7.6	0.49	J14	15	0.50
J6	7.5	0.47	J15	15	0.46
J7	7.5	0.65	J16	22.5	0.76
J8	7.5	0.43	J17	3.8	0.33
J9	26.6	0.49	J18	15	0.62

In this above situation, normally disassemble time will be high due to human intervention as well as disassemble efficiency will be lower than normal condition. Total disassembly time for module 1 can be estimated from the Table 2 and it is 255.8 s or 4.26 min. For J3, J7, J11, J16 Table 2 indicates higher value that means, HRC is not safer for human performing those disassembly tasks. In the Fig. 7, we presented disassemble job location on the module 1 and the position of human operator and robot.

Experimental results while non-game theoretic approach has been adopted is given in Table 6.

Table 6 depicts that total disassembly time is 230.3 s. or 3.83 min in normal condition. However, above results presented that, HRC model based on non-game theoretic approach is not safer for human operators. Therefore, it has been observed from this research that, Stackelberg game theoretic approach provides a better HRC model for disassembling such complex EOL devices.

suitable for HRC model and then we have designed the steps of disassembly process. For this, we have divided the entire device in 19 modules and after that, for each module we have identified disassembly jobs. Later than, we have assigned the disassembly jobs to disassembly resources based on their capabilities. Further, we have estimated utilities of disassembly resources by following the methodology of Zhou et al. [12]. Finally, we found game theoretic approach provided better solution than non-game theoretic approach even for complex disassembly set up.

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Human Performance in Human–Robot Interaction Contexts: Results from an Experimental Study



Mario Caterino , Marcello Fera , Marta Rinaldi ,
Valentina Di Pasquale , Raffaele Iannone , Roberto Macchiaroli ,
and Duc Truong Pham

Abstract This paper presents the results of an experimental study conducted in the field of human–robot interaction (HRI) aimed at evaluating the impact of the presence of a robot on human performance. Experiments were carried out in a virtual reality (VR) environment and were about a disassembly-reassembly task in the aerospace field. A sample of 78 engineering students participated in the project, divided into two subgroups, one working in co-existence with a robot and the other performing the same task without the presence of the robot. The parameter monitored during the experiments to compare the groups was the total completion time of the disassembly-reassembly task. The results obtained show that the two groups have similar behaviour. Statistically, there are no significant differences between the groups, and qualitative analyses show very similar behaviour concerning the learning experience on the task.

Keywords Human–robot interaction · Remanufacturing · Virtual reality · Experimental study

1 Introduction

The massive development of new technologies achieved during the fourth industrial revolution has changed and is still changing the characteristics of the human job. The implementation of technologies such as simulation [1], digital twins [2] and others [3, 4] has favoured the improvement of industrial system performance but has also

M. Caterino (✉) · V. Di Pasquale · R. Iannone
University of Salerno, 84084 Fisciano, Italy
e-mail: macaterino@unisa.it

M. Fera · M. Rinaldi · R. Macchiaroli
University of Campania, 81031 Aversa, Italy

D. T. Pham
The University of Birmingham, Edgbaston B152TT, UK

reduced human fatigue and increased safety in workplaces [5, 6]. Among these technologies, robots have a very important role because they can perform dangerous and repetitive tasks in place of human workers. The introduction of robots in industrial systems took place with the third industrial revolution, and today, half of the world-wide companies use robots for many production tasks to respond to high-volume demands [7]. In recent years, several degrees of interaction between human operators and robots have been developed in industrial contexts, leading researchers to study the consequences of such an interaction on humans. This discipline is called human–robot interaction (HRI) [8] in the scientific literature. Within the manufacturing context, HRI may lead to an increase in the flexibility, productivity and efficiency of production systems [9]. At the same time, ergonomic benefits are ensured [10] because of the reduction in the probability of developing musculoskeletal disorders due to dangerous and repetitive job activities. In production contexts, HRI has been explored in many fields, such as aerospace, where Rinaldi et al. demonstrated that an HRI production system can be more sustainable than a system exploiting only human capacities [11], automotive, where Teiwes et al. [12] demonstrated the possibility of improving assembly line performance, and logistics [13]. Additionally, in the remanufacturing context, HRI is proving to be valid. In particular, robots can cooperate with humans in the disassembly phase, reducing the costs of disassembly [14] by minimising the variabilities due to the different qualities of the returned products [15]. Huang et al. [16] proposed a framework for the realisation of a disassembly cell based on HRI, demonstrating that a high degree of flexibility can be obtained in such a cell. Liu et al. [17] considered the implementation of deep reinforcement learning and transfer learning in an HRI disassembly cell, demonstrating the effectiveness and sustainability of the cell. A complete review of the use of HRI for disassembly applications can be found in the paper by Hjorth and Chrysostomou [18].

Independent of the domain of application, industrial HRI still represents an open issue. The degree of acceptance of robots by human workers is still not clear. Robots may affect the psychological states of humans and generate emotions like anxiety, stress or frustration [19]. For this reason, it is essential to understand the impact of the implementation of HRI on humans and the negative emotions that could arise from the interaction. In fact, it is recognized that negative emotions at work can cause different changes in humans at various levels: emotional, cognitive, behavioral, or psychological [20]. Consequently, human performance can degrade; this is why the degradation of human performance can be considered an effect of HRI. This paper aims to investigate the impact of robots on human workers by conducting an empirical experiment to assess the behaviour of two different groups, one working with a robot in an HRI configuration and one working without the robot. In particular, the performance of the two groups is assessed in terms of the total completion time to accomplish a disassembly-reassembly task. Previous studies on this topic have demonstrated the positive impact of robot introduction on human workers' performance, particularly considering ergonomics and productivity [11, 21]. Productivity increases because of the reduction of the takt time since robots handle tasks that can be carried out faster than humans [21]. However, productivity represents a direct measure of the production system performance, and an increase in productivity can

also be achieved by worsening human performance, which is instead affected by several other factors related to trust, such as mental stress, anxiety and acceptance of the robot [22, 23]. This is the reason why, often, more accurate analyses are needed to assess only human performance (not system performance) in HRI systems. Caterino et al. [24] proposed a human error analysis in the HRI context for this purpose. Their results demonstrate that there is no significant difference in the number of errors made during a working task by a group interacting with a robot during the working tasks and one noninteracting group. A similar result was achieved in the experiment by Huber et al. [25], who observed that no significant differences can be found between two groups performing a hand-over task, one in a human–human configuration and one in a human–robot configuration. On the other hand, some studies defend a different thesis, arguing that humans are affected by the presence of the robot. Zhang et al. [26] demonstrated that humans' behaviour changes when they interact with a robot, with clear consequences on the performed activity; Lu et al. [27] analysed some physiological factors (heart rate, oxygen level, etc.) in human operators performing activities in an HRI configuration, finding that feelings of anxiety and surprise were often present during the interaction.

This paper will provide further evidence for one of the two contrasting theses by statistically evaluating the difference between the two groups previously mentioned and providing some insights based on qualitative observations of the results. These evaluations will be performed by looking at the total completion times of an aerospace task performed by the 2 different groups.

2 Description of the Experimental Setting

An experimental study was conducted to assess whether the presence of a robot has an impact on human performance. The full details of the experiment can be found in Caterino et al. [24]. The study was conducted in a laboratory environment at the beginning of 2023 and was carried out by respecting the ethical principles of the Declaration of Helsinki of 1975 [28]. Experiments were realised using a virtual reality (VR) system. VR systems allow the reproduction of the real production environment and ensure a quick, safe and economical interaction between humans and robots. The use of VR has been validated over the years for HRI activities, and it has proven to represent an effective tool for performance assessments in the HRI context [29]. For the realisation of the virtual environment, the HTC Vive Pro[®] system was used, while Unity software was used to build the objects and the interactions among players. The degree of interaction between humans and robots in this scenario is coexistence [30]. In a coexistence environment, human operators and robots share the same workspace, but they cannot have any physical contact. To each actor (humans and robots), specific tasks are assigned, and they cannot collaborate on common tasks.

The task to carry out is in the aerospace field. It concerns the disassembly, application of sealant and reassembly of a fuselage panel. For confidentiality reasons, more details of the task cannot be revealed. During the execution of the task, participants

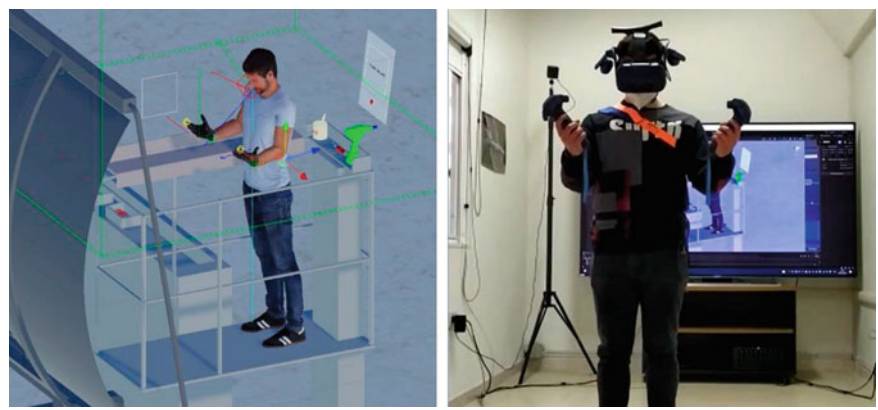


Fig. 1 Representation of the real and virtual environments

use several tools. A reproduction of the real and virtual environment is shown in Fig. 1.

Two scenarios have been simulated: in the first one (scenario #1), people perform the task in a co-existence environment with a robot. For this study, the reproduction of a Fanuc M20iA was used. In the second scenario (scenario #2), people perform the task without the presence of the robot. Hence, the task carried out by the participants in scenario #1 and scenario #2 is the same, and the only difference is the presence or absence of the robot.

People participating in the project were students from the Department of Engineering (mainly industrial, aerospace or mechanical engineering students). Overall, 78 students were involved in the study (33 females and 45 males). The mean age of the student population was 24.8 years, with a standard deviation of 3.49 years. Students were divided into 2 groups, namely, the group performing the experiments in scenario #1 (called the HRI_coex group) and the group performing the experiments in scenario #2 (called the NO_HRI group). More details on the composition of the groups are given in Table 1.

Upon arrival at the laboratory, each participant was introduced to the context of the experiment by watching a short video, which was also useful as a means of training for the VR system. Then, the participants were requested to sign a consent form before starting the experiment and were randomly assigned to one of the two groups (balancing only the sex). Before starting the experiment, participants were not

Table 1 Characteristics of the groups

	HRI_coex	NO_HRI
Number of male participants	23	22
Number of female participants	16	17
Mean age of participants (years)	24.5	25.1
Standard deviation of age (years)	3.49	3.49

aware of the group to which they belonged; thus, they were not informed about the presence of the robot. Each participant repeated the experiment 4 times. The multiple repetitions were useful both to acquire confidence with the VR tool and for evaluating some learning aspects of the task. During the execution of the task, participants were recorded for successive analyses by expert engineers and researchers.

2.1 Data Collection and Statistical Analysis

The purpose of the paper is to evaluate if there are significant differences between the two groups by comparing the completion times of the task briefly described in the previous section. For this purpose, the recorded videos of the study were analysed, and the times for completing the entire task were retrieved for each participant using an appropriate time measurement method applied by expert engineers and researchers. This allowed us to obtain independent data, which can be statistically analysed to assess possible differences between the groups.

Statistical analyses were performed to compare the data related to the two groups. A two-tailed independent t-test was used to compare the means of the two groups [31]. Before carrying out the t-test, it must be ensured that the data of the two groups follow a normal distribution and that the variances (or standard deviations) are not significantly different (homogeneity of variances). To analyse the normal distribution of the data, a Shapiro–Wilk test was used. To verify the homogeneity of variances, an F-test was carried out.

All statistical analyses were performed using the software Rstudio®.

After the statistical analyses, some qualitative insights about the behaviour of the two groups were retrieved by realising and analysing the boxplots of the completion times.

3 Results

This section reports the results of the experiments. As mentioned, the participants were divided into 2 groups, namely, group #1 (HRI_coex), performing the task in the presence of the robot, and group #2 (No_HRI), performing the test without the robot. To statistically compare the means of the two groups using a t-test, the data must have the same statistical distributions. Thus, the first test performed was the Shapiro–Wilk test, which is used to verify that a given sample of data follows a normal distribution. Table 2 reports the results of the Shapiro–Wilk test.

The third and fourth columns of the table report the W-statistic and the p-value. Both give indications about rejecting the null hypothesis of the Shapiro–Wilk test, i.e., the hypothesis that data are Normally distributed. The parameter W varies in a range between 0 and 1. When the significance level is fixed, high values of the W-statistic parameter, near 1, provide evidence that it is not possible to reject the

Table 2 Results of the Shapiro–Wilk tests

Experiment number	Group	W-statistic	p-value
#1	HRI_coex	0.978	0.590
#2	HRI_coex	0.982	0.735
#3	HRI_coex	0.957	0.094
#4	HRI_coex	0.945	0.079
#1	NO_HRI	0.986	0.879
#2	NO_HRI	0.961	0.208
#3	NO_HRI	0.970	0.375
#4	NO_HRI	0.978	0.633

null hypothesis. The p-value also measures the evidence against the null hypothesis, giving information about the probability that the observed data occur if the null hypothesis is true. In the case of this research, fixing a significance level of 0.95, a p-value lower than 0.05 would allow rejecting the null hypothesis. From Table 1, none of the p-values are lower than 0.05, indicating that the null hypothesis of the Shapiro–Wilk test cannot be rejected. Thus, the observed data can all be considered to follow a normal distribution.

This can also be demonstrated by plotting the histograms representing the total completion time of each participant versus the expected normal curve for a given mean and standard deviation, as in Fig. 2, where the histograms of the first experiment have been represented for each group. It is possible to note that they generally follow the theoretical normal distribution. The histograms of the other experiments have a similar shape.

Once the normality of the distributions was verified, a first comparison between the groups was performed to evaluate whether there were differences that could be noted without the help of statistical analysis.

Table 3 reports the means and standard deviations of the total completion times for each experiment and each group, which will also be useful for the successive F-test and t-test.

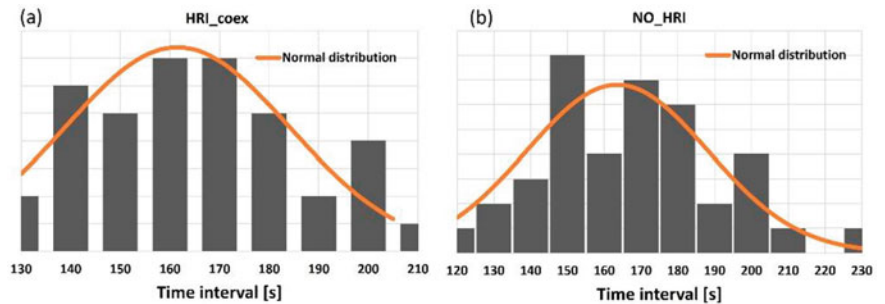


Fig. 2 Histograms of the completion times for the first experiment of the groups

Table 3 Mean and standard deviation of the completion times

Experiment number	Mean completion time HRI_coex [s]	Mean completion time NO_HRI [s]	Standard deviation HRI_coex [s]	Standard deviation NO_HRI [s]
#1	161.5	163.5	22.9	24.9
#2	103.3	98.9	16.0	12.0
#3	88.4	87.0	9.9	10.1
#4	85.5	84.7	10.1	11.5

A first analysis of Table 2 seems to highlight a very similar behaviour between the two groups, which both decrease the completion times and the standard deviations when repeating the experiments. To statistically confirm this hypothesis, a two-tailed independent t-test must be performed. The realisation of the t-test requires, in addition to the normal distribution of the analysed data, that the variances (or standard deviations) of the groups are homogeneous (homoscedasticity).

To verify the homogeneity of the variances, a 2-tailed F-test was performed. The null hypothesis is that the variances of the groups are homogeneous, while the alternative hypothesis is that the variances are different. Table 4 reports the results of the F test for each group and each experiment.

For the same significance level assumed before (95%), the p-value is still greater than 0.05 for each experiment; only for experiment #2 the p-value is close to 0.05. For such an experiment, the F-statistic, representing the ratio between the variances of the groups, is also higher than 1.7, highlighting a greater difference between the variances of the two groups. However, the p-value is greater than 0.05. Thus, there is no evidence to reject the null hypothesis, and all the conditions to conduct the t-test have been met.

The null hypothesis of the t-test is that there are no significant differences between the means of the completion times of the two groups; the alternative hypothesis is that there are differences in the means of the observed data between the groups. Table 5 reports the results of the t-test for each group and each experiment.

The t-statistic is negative for the first experiment and then positive for the others. This is because the first experiment is the only one in which the mean of the group performing the experiment without the robot is greater than that of the other group (Table 3). Concerning the p-value, once again, considering a significance level of 95%, it is always greater than the value to reject the null hypothesis (0.05). Hence,

Table 4 Results of the F tests to verify the homogeneity of variances

Experiment number	F-statistic	p-value
#1	0.846	0.598
#2	1.775	0.081
#3	0.965	0.926
#4	0.785	0.476

Table 5 Results of the t-tests

Experiment number	t-statistic	p-value
#1	−0.381	0.704
#2	1.400	0.166
#3	0.560	0.577
#4	0.314	0.754

there is no evidence for rejecting the null hypothesis, and it can be concluded that there are no significant differences between the two groups concerning the means of their completion times for each experiment.

This conclusion can also be qualitatively reached by observing Fig. 3, where the boxplots of each experiment for each group are shown.

By comparing the boxplots of the two groups in each experiment, it is evident that the medians and interquartile distances are very similar, as well as the whiskers of the boxplots. This is a further graphical demonstration of what was already demonstrated by the F test, the t-test and the values reported in Table 3: the two groups are not different in their behaviour.

In Fig. 3, it is interesting to note that the values of the medians decrease when the repetition of the experiments increases, as do the interquartile distances. This is due to the learning factor that is applied by repeating the experiments, which reduces the completion times and their variances. In particular, passing from the first (Fig. 3a) to the second (Fig. 3b) experiment, the median completion time is reduced by 37% for the group performing the activity with the robot and by more than 40% for the

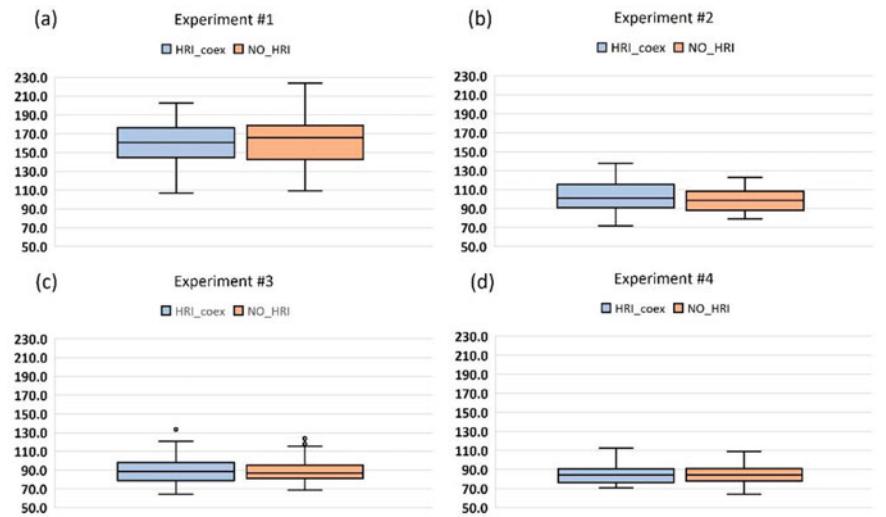


Fig. 3 Boxplots of the completion times for each experiment

Table 6 Medians and interquartile range reductions

	Experiment #1–#2 (%)	Experiment #2–#3 (%)	Experiment #3–#4 (%)
<i>HRI_coex</i>			
Median reduction	37.1	12.4	4.9
Interquartile range reduction	22.3	34.6	10.0
<i>NO_HRI</i>			
Median reduction	40.5	12.2	2.3
Interquartile range reduction	44.6	33.8	3.4

group without the robot. The medians also decrease when passing to the third and fourth experiments, as well as the interquartile range.

These results are summarised in Table 6.

This phenomenon is probably due to a double effect: the learning of the task to perform and the learning of the VR tool used for the study. At this stage of the study, it was not possible to discriminate these two effects, but future developments may investigate these aspects.

However, it is interesting to note how the median reduction tends to decrease when the number of experiments increases for both groups (as well as the mean shown in Table 3). This allows us to conclude that after an initial adaptation to the task, participants had a strong learning phase, which led to an improved way of carrying out the activities. This can be noted by observing that the difference between the medians of the third and fourth experiments is very low, pointing out that the learning phase is decreasing already starting in the fourth experiment.

The same can be noted for the interquartile range reduction, which represents the percentage of reduction of the interquartile range (the height of the boxes) when passing from experiment i to experiment $i + 1$.

Figure 3 and Table 6 further demonstrate the similarity between the two groups. In fact, in addition to the similarities of the boxplots shown in Fig. 3, Table 6 allows us to conclude that the learning patterns of the two groups are very similar, implying that the presence of the robot has very limited or no effects at all on the HRI_coex group.

4 Discussion and Conclusions

The results achieved by this paper contribute to the literature in different ways. The paper has a very clear position, supporting the thesis that the presence of robots does not affect (negatively or positively) the performance of the human operator. This is in line with the other analysis made by Caterino et al. [24], who demonstrated

that the HRI_coex and NO_HRI groups are statistically similar when considering the number of errors made during the execution of the same industrial task. This result is also consonant with Morioka and Sakakibara [10], which concluded that human productivity in coexistence is comparable to human productivity alone, when the robot does not interfere directly with the human's physical motions or attention. It is important to note that the results achieved in this paper do not express that the introduction of the robot in a working environment does not improve the performance of the production system. Many authors [9, 11, 21] have demonstrated that the productivity of production systems increases, and this paper confirms this. In fact, by demonstrating that the human operators' performance remains the same independently of the presence of the robot, this paper indirectly demonstrated also the effectiveness of the introduction of robots in a working environment: if the assignment of tasks to the robots allows a reduction in the cycle time for the production of an item or to have a higher final quality, it is easy to understand that the neutrality of the human performance towards the presence of the robot does not affect in any way the improvements achieved.

On the other hand, the results achieved in this paper seem to be discordant with that part of the literature claiming that the presence of robots creates a different behaviour in human operators. This difference can be in part explained by looking at the parameters monitored during the experiments. In fact, in this paper, the completion time of the task was used as the parameter to assess human performance, but no data are available on physiological factors, such as the heart rate or the oxygen level, which would have been useful to identify stress and anxiety, as in the case reported by Lu et al. [27]. Thus, it is not possible to conclude that the presence of the robot had no effect at all, but it can be concluded that it had no effects on a macroscopic parameter, such as the completion time.

In conclusion, the present paper aimed to evaluate the impact of the presence of a robot on human performance in an HRI co-existence context by evaluating the differences in the completion times of 2 groups performing the same task with and without the robot. The results highlight that there are no statistically significant differences between the two groups of participants. The F-test and t-test conducted to evaluate, respectively, the differences in the variances of times and the differences in the means gave a clear indication: the two groups can be considered very similar. This thesis was also reinforced by some qualitative analysis, which demonstrated that the learning phase is very similar for both groups. On the other hand, the parameter monitored, i.e., the completion time, does not give any evidence about some possible feelings that can be induced in the human operator by the presence of robots, such as anxiety, stress or surprise. This represents one of the limitations of this paper. A second limitation is related to the fact that only the total completion times of the task were analysed for each group, without a focus on the times of the individual operations of the task, which can provide more information. Finally, it should be assessed whether the use of the VR tool may create a bias in the analyses for two reasons. The first one is that simulated robot may not be perceived the same as a real robot by the participants: working in a simulated environment let people feel reassured that nothing can go wrong. The second reason is that, even if a similar

behaviour was observed between the two groups concerning their learning phase, it was not possible to discriminate between the learning of the task to perform and the learning of the VR tool used.

All these aspects will be investigated in future work on this theme.

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Cognitive Digital Twin Modeling of Robotic Disassembly Process



Lei Qi, Hang Yang, Jiayi Liu, Wenjun Xu, and Yi Zhong

Abstract With the increasing concern of recycling the end of life products, robotic disassembly is being paid much attention nowadays. Generally, there are many uncertainties in disassembly process, and these uncertainties should definitely be considered. Cognitive capability forming is useful to solve the uncertainties during the robotic disassembly process. In this paper, cognitive digital twin model of robot disassembly process is built, and its cognitive capability is validated. An ontology modeling-based method is proposed to achieve the cognitive capability of the digital twin. During the robotic disassembly process, the cognitive capability addresses uncertainties of different fasteners with similar product structure. In order to verify the proposed method, the case studies are conducted in robotic disassembly process of clutches, and results show that cognitive digital twin is able to resolve the uncertainties of product fasteners in the robot disassembly process and improved the success rate in disassembling the products with similar structure.

Keywords Cognitive digital twin · Modeling · Disassembly · Industrial robots

1 Introduction

The digital twin was first introduced by Professor Grieves of the University of Michigan and it was regarded as a conceptual model for product lifecycle management [1]. Afterwards, Glaessgen and Stargel established a more comprehensive definition of digital twin and they stated that digital twin was the simulation process that integrated multiple disciplines, physical quantities, scales, and probabilities based on physical models and perception data [2]. Digital twin reflects the full lifecycle process of a physical entity by completing the mapping in virtual space. Enhanced

L. Qi (✉) · H. Yang · J. Liu · W. Xu · Y. Zhong

School of Information Engineering, Wuhan University of Technology, Wuhan 430070, China

e-mail: qilei53@whut.edu.cn

Hubei Key Laboratory of Broadband Wireless Communication and Sensor Networks, Wuhan University of Technology, Wuhan 430070, China

by semantic capabilities, cognitive digital twin (CDT) is a hybrid and self-learning system that will optimize its own cognitive capabilities over time based on the data and experience that it collects [3]. However, digital twin is a digital model of a physical system that captures attributes and behaviors of that system [4]. CDT combines cognitive features to perceive complex and unpredictable behaviors and realizes reasoning using optimal strategies [5]. Ontology in CDT plays a key role in semantic modeling, and it is a key enabling method to achieve the cognitive capability [6, 7]. When using cognitive models, the ontology is the basis to support unified knowledge description and CDT integration among each sub-model across the entire system. Digital twin enriched by cognitive capabilities helps to learn new knowledge from dynamic and uncertain environments.

Remanufacturing helps to reduce environmental pollution and improves resource utilization. Disassembly is a necessary link in reverse supply chain and plays a significant role in remanufacturing, and there are lots of uncertainties in disassembly process. Recently, robotic disassembly is being paid much attention due to its programmability and universality. Because of the uncertainties and complexity of the product disassembly process, robots that rely on user input for positions of components to disassemble is unable to perceive and reason about product structure. Furthermore, the robotic disassembly system is only designed for the same product and could not be used to disassemble different products. Most of the existing methods for modeling robotic disassembly process rely on foreknowledge. Those methods are difficult to adjust dynamically to the uncertainties and dynamics of robotic disassembly process. However, CDT could obtain new knowledge from perceived data [8] of robotic disassembly process. Based on this, it dynamically updates the disassembly process model and helps to achieve more reliable disassembly decisions. In view of this, the cognitive capability of CDT would address the challenges of uncertainties in robotic disassembly process. In the modeling of robotic disassembly process, CDT helps to enhance the following capabilities: (1) Enhance cognition of uncertain environment during robotic disassembly process through applying an updatable ontology to simulate human cognitive capability. (2) Reason to obtain new knowledge of robotic disassembly process and historical data, since the use of CDT structure provides generic information for basic disassembly of unknown products.

The rest of this paper is organized as follows. The related works are summarized in Sect. 2 and the architecture of CDT model for robotic disassembly process is introduced in Sect. 3. In Sect. 4, CDT of multidimensional model in robotic disassembly process is constructed and CDT model is validated by the case study based on fasteners of different clutches in Sect. 5. Finally, the cognitive functions of CDT, its features and shortcomings in robotic disassembly process are summarized in Sect. 6.

2 Related Works

This section reviews the existing cognitive digital twin models and knowledge modeling approaches in manufacturing in terms of digital twin modeling of the disassembly process and disassembly capability modeling.

Liu et al. used graph-based method and matrix-based method to build the disassembly model of end of life (EOL) products. A service platform for remanufactured robot disassembly model was built, and physical robots could be integrated with the robotic disassembly planning method [9, 10]. Tian et al. modeled the profit and energy consumption of disassembly process, and dual-objective optimization was utilized to optimize these goals considering multiple constraints [11]. The main challenge for robotic disassembly is the uncertainties of product structures, models, and conditions [12]. Foo et al. proposed a cognitive model for expanding the generic ontology of future disassembly process by using previous disassembly experiences [13]. This research applied an automatically expandable ontology to imitate learning in order to solve the uncertainties of disassembly process. Ramirez et al. [14]. presented a model for the economic assessment of the robotic disassembly process of EOL products. It is able to re-plan the optimal disassembly process level depending on the process uncertainties. Existing disassembly modeling approaches are not tightly integrated between physical space and cyberspace. The disassembled parts are also not modeled during the disassembly process. Due to the uncertain status of EOL products, it is unlikely that all potential scenarios will be completely modeled [15]. And less research has been conducted on digital twin modeling of disassembly process of industrial robots.

DT has been applied to various applications such as assembly, manufacture, Aerospace manufacturing, etc. DT can be used to monitor and control the quality of products through multi-scale quality analysis. Liu et al. [16] proposed a method constructed the digital twin quality knowledge model from the macro, meso, and micro levels by utilizing the data of the digital twin mimic model. Bao et al. [17] used Automation Markup Language for modeling a structural parts machining cell. Yang et al. [18] integrated the digital twin, Gaussian mixture, and the hidden Markov model. The model can dynamically predict the generation of disassembly waste under uncertainties. Existing methods lack the study of modeling process. Modeling the robotic disassembly process with DT is still blank. How to achieve the existing approaches with disassembly data in robotic disassembly process is critical to DT.

From the perspective of cognitive capability, Zheng et al. [19] summarized the definition and characteristics of CDT. It was defined as a digital representation that has cognitive capability and autonomy. According to the ISO 42010 standard, Lu et al. [20] designed a conceptual architecture to support CDT model development and proposed an application framework enabled by a knowledge graph is provided to guide the CDT applications. D'Amico et al. [21] provided an ontological approach to develop DT and improve maintenance management leading to the creation of DT or CDT. It also pointed out that using a top-level ontology approach should be the starting point for the creation of CDT. Cognitive capability is reinforced by learning

historical data and events in manufacturing. Abburu et al. [4]. developed a digital twin of the process and it was used to develop models with cognitive capabilities for self-learning and predictive maintenance. Nevertheless, there is a lack of unified reference architectures to support CDT development. This paper addresses uncertainties of robotic disassembly process through the application of the cognitive capability in CDT, which has not been achieved in the disassembly domain before this work.

3 CDT Architecture of Robot Disassembly Process

The CDT architecture of robotic disassembly process in this paper includes a digital model module, cognitive module, and data interaction module as shown in Fig. 1.

The data interaction module is the bridge between CDT model and the physical space. The disassembly data of robots is collected by physical devices (e.g. force sensors, Vernier calipers, cameras, power meters, etc.). The cognitive twin of robotic disassembly process gets the required data to update its state in real-time based on data communication protocols (e.g. TCP/IP, OPC-UA and MTConnect, etc.). EOL product information is sent to the ontology as Excel files and imported into disassembly ontology using Cellfie in Protégé. After the whole disassembly process is completed, the disassembly ontology is expanded with the data of the disassembly process, thus improving the cognitive capability of CDT system.

The digital model module includes four dimensions: geometric, physical, behavior, and rule models of physical space entities. The digital model is designed to be modular. It could be applied to other environments through improving these

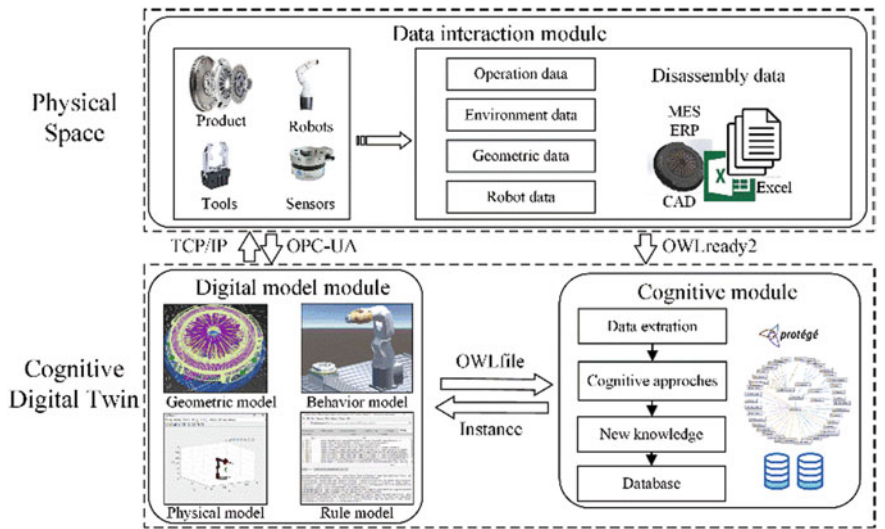


Fig. 1 CDT architecture of robotic disassembly process

modules. During the disassembly process of a series of unknown products, the digital model module gets updated information from the ontological structure in the cognitive module. After ontology modeling is completed, the model feature data of all four dimensions are saved in an OWL (Web Ontology Language, OWL) file as ontology instances. A new DT is created by using the OWL instance data.

The cognitive module consists of robotic disassembly process ontology and a database of previous disassembly process. The ontology is built using Protégé version 5.6.0 open-source software. The ontology of the cognitive module is used to store conceptual knowledge, and the database stores disassembly experiences to help update conceptual knowledge. It can represent generic disassembly concepts (product sequence, components, fasteners, disassembly operations, execution time), and it also describes the way they are related to each other. The cognitive module identifies component types, fastener types, and the robotic disassembly operations recommended for disassembling fasteners. It is also possible to apply the knowledge gained with CDT to other similar products. The database then records information on the components of the EOL product during each disassembly process: product type and ID; a list of fastener types and their coordinates and dimensions of each fastener; geometries, coordinates and dimensions of each component; disassembly sequence; other features (mass, color, rigidity, etc.).

4 Enabling Technologies

Cognitive digital twin of robotic disassembly process is built in terms of cognitive, geometric, physical, behavior and rule models, as shown in Fig. 2.

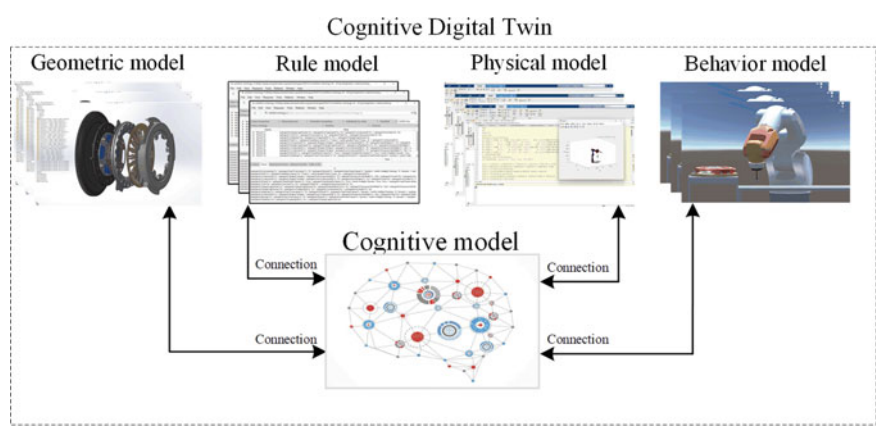


Fig. 2 Cognitive digital twin model

4.1 Cognitive Model

The cognitive models correspond to digital models and physical entities of each dimension. Each model has its corresponding ontology describing their features and properties in the cognitive model. And the object relationships between the different models are defined in OWL files, as expressed by Eq. (1).

$$OWL = \sum \{Geometric, Physical, Behavior, Rule, EOL\_Product\} \tag{1}$$

The robot disassembly process ontology for the cognitive model is built by using Protégé. Generic classes, object properties, data properties of products, robots and disassembly process are reasoned by Pallet in Protégé. In terms of ontology expansion, new information from the disassembly process is implemented into the ontology using the Owlready2 API Python library, which is able to edit the ontology structure. The structure of cognitive model is shown in Fig. 3.

By editing the ontology structure, past disassembly process data expands the cognitive model to enhance its cognitive capability. Although the appearance and location of components and fasteners are different, they can be inferred from

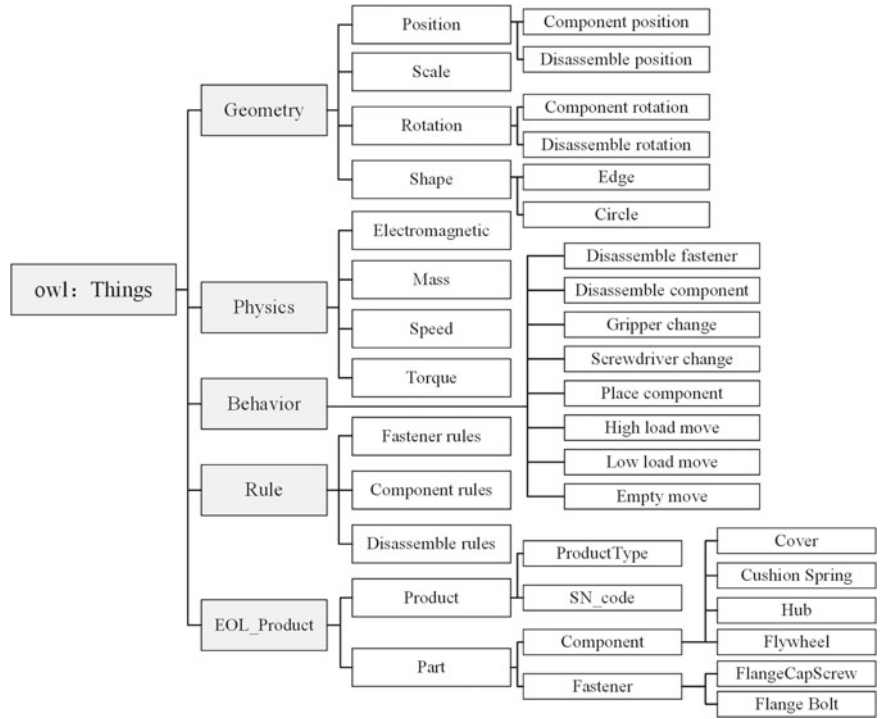


Fig. 3 Cognitive modeling structure

other characteristics. Afterwards, the cognitive model infers the correct disassembly sequence and component types from connectivity relationships and rules generated from previous run data.

4.2 Geometric Model

Geometric model is built using 3D modeling software (AutoCAD, 3ds MAX, SolidWorks, etc.). It includes 3D models of robots, components, fasteners, tools, geometric parameters, and position relationships between the components. Dimension is defined based on the mesh file. The position is defined as the spatial location in the world coordinate in robotic disassembly system, including the three parameters X, Y and Z. The angle parameter is the rotation angle of the basic coordinate system relative to the world coordinate system around X-axis, Y-axis and Z-axis, including three parameters A, B and C. Finally, the geometric model is imported into Unity3D to anchor the robot position, component position, disassembly position, and placement position. In addition, the geometric model contains geometric constraints and the space interference matrix for robotic disassembly process.

4.3 Physical Model

Since physical entities contain a variety of physical attributes, the physical properties that are closely related to robotic disassembly process would be selected for modeling, such as mass, acceleration, velocity, torque, friction coefficient, energy consumption, stress, electromagnetism, and other physical properties. In this paper, due to the experimental constraints, only the dynamics of the industrial robot during disassembly are considered to simulate the robot joint torque.

The robot dynamics model uses Simulink in Matlab to simulate the torque by Eq. (2), and the mass is collected through a force sensor at the end of the joint.

$$\tau(t) = D(q(t))\ddot{q}(t) + h(q(t), \dot{q}(t)) + G(q(t)) \quad (2)$$

$\tau(t)$ is the vector formed by torque of each joint. $q(t)$ is the vector formed by angular variables of each joint. $\dot{q}(t)$ is the vector formed by velocity of each joint. $\ddot{q}(t)$ is the vector formed by acceleration of each joint. $h(q, \dot{q})$ is the vector formed by Coriolis Force and centrifugal force of each joint. $G(q)$ is the vector formed by gravity of each joint. $D(q)$ is the mass matrix of the robot.

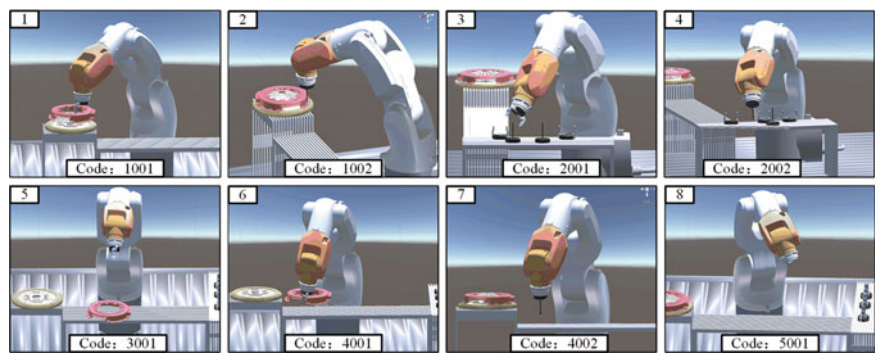


Fig. 4 Behavior model

4.4 Behavior Model

The behavior model divides the necessary behaviors in robotic disassembly process according to their functions, and the disassembly tasks are performed by assembling these behaviors. Robotic disassembly behaviors include: 1. Disassemble component; 2. Disassemble fastener; 3. Gripper change; 4. Screwdriver change; 5. Place component; 6. High load move; 7. Low load move; 8. Empty move. Each type of behaviors has a code used as the action command for industrial robot, as shown in Fig. 4. When the code is transmitted from cyber space to physical space through the communication interface. The code triggers predefined functions to complete robot related behavior in Fig. 4 through KR C4 controller.

4.5 Rule Model

The rule model is constructed using open semantic description languages such as Web Ontology Language (OWL) and Semantic Web Rule Language (SWRL). More complex rules are set between classes, object properties, and data properties using SWRL rules. SWRL rules contain a series of atoms and operators to form an antecedent (body) and consequent (head). If all the conditions of the antecedent are true, the condition of the consequent is true.

Concepts like fastener types are encapsulated into classes and relationships between classes are defined by object properties. Concepts like mass, size, position, etc. are defined using data properties. The essential rules of robotic disassembly process are shown in Table 1. For example, the second rule in the table indicates:

(1) Is a component; (2) Has a circle shape; (3) The hub is under it and the flange screw is on top of it; (4) Has a size between 200 and 250.

If all of the above conditions are satisfied, the component is determined to be the clutch cover.

Table 1 SWRL rules of robotic disassembly process

<i>Rules of robotic disassembly process</i>	
• $\text{Part}(\text{?c}) \wedge \text{hasMassValue}(\text{?m}, \text{?mass}) \wedge \text{swrlb:greaterThan}(\text{?mass}, 4) \rightarrow \text{Component}(\text{?c})$ • $\text{Component}(\text{?c}) \wedge \text{Circle}(\text{?shape}) \wedge \text{isComponentOf}(\text{?c}, \text{?p}) \wedge \text{hasShape}(\text{?c}, \text{?s}) \wedge \text{Hub}(\text{?p}) \wedge \text{isUnder}(\text{?p}, \text{?c}) \wedge \text{FlangeCapScrew}(\text{?g}) \wedge \text{isToppingOf}(\text{?g}, \text{?c}) \wedge \text{Size}(\text{?c}, \text{?d}) \wedge \text{swrlb:greaterThan}(\text{?d}, 200) \wedge \text{swrlb:lessThan}(\text{?d}, 250) \wedge \text{DisassemblyState}(\text{?c}, 0) \rightarrow \text{Cover}(\text{?c})$ • $\text{FlangeCapScrew}(\text{?a}) \wedge \text{FlangeCapScrew}(\text{?b}) \wedge \text{isRelativeTo}(\text{?a}, \text{?b}) \wedge \text{DisassemblyState}(\text{?a}, \text{?aa}) \wedge \text{DisassemblyState}(\text{?b}, \text{?bb}) \wedge \text{DisassemblyList}(\text{?a}, \text{?listA}) \wedge \text{DisassemblyList}(\text{?b}, \text{?listB}) \wedge \text{swrlb:notEqual}(\text{?aa}, \text{?bb}) \wedge \text{swrlb:equal}(\text{?aa}, 0) \rightarrow \text{RobotDisassemblyState}(\text{KR3\_KR540}, \text{?listA})$ • $\text{Component}(\text{?c}) \wedge \text{Shape}(\text{?shape}) \wedge \text{isComponentOf}(\text{?c}, \text{?f}) \wedge \text{DisassemblyState}(\text{?c}, \text{?dc}) \wedge \text{Hub}(\text{?h}, \text{?hhs}) \wedge \text{isUnder}(\text{?c}, \text{?h}) \wedge \text{swrlb:greaterThan}(\text{?ccs}, \text{?hhs}) \rightarrow \text{Flywheel}(\text{?c})$ • $\text{Robot}(\text{?c}) \wedge \text{hasElectricValueA}(\text{?c}, \text{?cca}) \wedge \text{hasElectricValueV}(\text{?c}, \text{?ccv}) \wedge \text{swrlb:multiply}(\text{?power}, \text{?cca}, \text{?ccv}) \rightarrow \text{hasPowerValue}(\text{?c}, \text{?power})$ • $\text{Gripping}(\text{?c}) \wedge \text{hasTimeValue}(\text{?c}, \text{?t}) \wedge \text{Robot}(\text{?r}) \wedge \text{hasPowerValue}(\text{?r}, \text{?power}) \wedge \text{swrlb:multiply}(\text{?energy}, \text{?t}, \text{?power}) \rightarrow \text{hasEnergyValue}(\text{?c}, \text{?energy})$ • $\text{Moving}(\text{?c}) \wedge \text{hasTimeValue}(\text{?c}, \text{?t}) \wedge \text{Robot}(\text{?r}) \wedge \text{hasPowerValue}(\text{?r}, \text{?power}) \wedge \text{swrlb:multiply}(\text{?energy}, \text{?t}, \text{?power}) \rightarrow \text{hasEnergyValue}(\text{?c}, \text{?energy})$ • $\text{Unscrewing}(\text{?c}) \wedge \text{hasTimeValue}(\text{?c}, \text{?t}) \wedge \text{Robot}(\text{?r}) \wedge \text{hasPowerValue}(\text{?r}, \text{?power}) \wedge \text{swrlb:multiply}(\text{?energy}, \text{?t}, \text{?power}) \rightarrow \text{hasEnergyValue}(\text{?c}, \text{?energy})$ • $\text{FlangeCapScrew}(\text{?a}) \wedge \text{isToppingOf}(\text{?a}, \text{?b}) \wedge \text{Component}(\text{?b}) \rightarrow \text{isUnder}(\text{?b}, \text{?a})$	

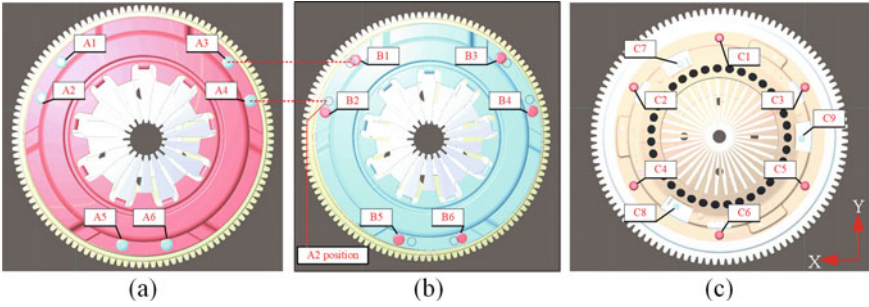


Fig. 5 The connection between cyber and physical space

4.6 Connection

From physical to cyber space, the data of industrial robot and condition of the product is transmitted. The data of industrial robot includes joint torque, Cartesian coordinates of the end and joint angle. Condition of the product contains disassembly sequence and disassembly torque. JOpenShowVar communication is provided to transmit the data from physical to cyber space, as shown in Fig. 5.

As for the cyber to physical space connection, the command of robotic disassembly process is transmitted. Disassembly action is generated by disassembly ontology. The action is encoded as code series from Fig. 4. For example, if the first fastener will be disassembled, code “5001; 2002; 5001; 1002; 4002; 3001” is generated. The action codes of action are sent to KR C4 using JOpenShowVar communication method. After that, the disassembly process of the physical robot is realized.

5 Case Study

As mentioned above, the proposed CDT disassembly process model is validated in this paper. The experiments were conducted using the robot KR 3 R540 with the required tools. The robot performed the task of fasteners disassembly of the clutch cover and executed the robotic disassembly process in three different types of clutches. Clutches A and B only have different fastener positions on the clutch cover. The distance between fasteners A1 and A2 is less than the distance between fasteners B1 and B2 in Fig. 6 as well as other fasteners in Clutches A and B. The fasteners of Clutch C are symmetrically placed, and Clutch C has different type of component than Clutches A and B. The information of all fasteners in A, B, and C is shown as Table 2.

The geometric center of product is used as the reference point for component coordinates for reasoning the position relationship. If the sum of the position vectors of two or three fasteners in the XY plane is zero vector, they will be considered as

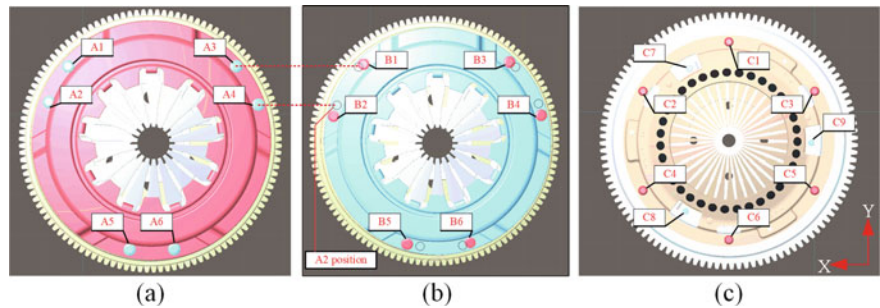


Fig. 6 Clutches for testing. a Clutch A. b Clutch B. c Clutch C

Table 2 Fasteners information in Clutches A, B, and C

Fastener	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6
Mass (g)	7	7	7	7	7	7	7	7	7	7	7	7
Sequence	1	4	5	2	3	6	1	4	5	2	3	6
Position X (mm)	77	97	-77	-97	20	-20	75	99	-75	-99	24	-24
Position Y (mm)	67	33	67	33	-100	-100	66	32	-66	32	-98	98
Fastener	C1	C2	C3	C4	C5	C6	C7	C8	C9			
Mass (g)	5	5	5	5	5	5	4	4	4			
Sequence	1	3	5	6	4	2	7	8	9			
Position X (mm)	0	97	-97	97	-97	0	50	50	-100			
Position Y (mm)	112	56	56	-56	-56	-112	86	-86	0			

relative fasteners, such as “A1, A4, A5”, “C1, C6” and “B1, B4, B5”. The components with relative relationships should be disassembled simultaneously. Because disassembling in sequence described above allowed other fasteners and components to be evenly stressed. This would help the rest of the robotic disassembly process and increase the success rate of subsequent disassembly. When they are not disassembled at the same priority, the clutch cover will have the error angle to affect the following disassembly steps, as shown in Fig. 7.

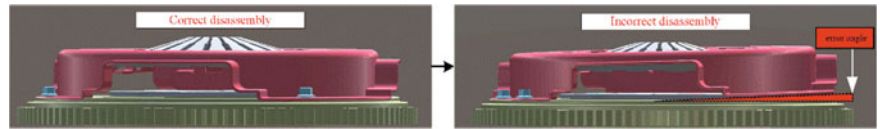


Fig. 7 Comparison of correct disassembly and incorrect disassembly results

Regarding different products, the disassembly process model is updated according to the product characteristics. For example, when replacing the product to be disassembled on the workbench from Clutch A to C, new component and fastener instances are added to disassembly ontology. Then the geometry model and component coordinates of Clutch C are updated in the digital twin. Tools and components have also been updated, as shown in Fig. 8. At the same time, the robotic paths and behaviors have been updated for robotic disassembly process based on the product changes.

The disassembly process of Clutch A was simulated ten times in the CDT. The “before” and “after” columns in the Table 3 compare the results of the original ontology with the results after running ten times. Clutch C was simulated ten times on the basis of the new ontology generated by Clutch A for comparison. The results are shown in Table 3. The meaning of Component identification in the table is the identifications of the four main components in each clutch, which are identified by the rule model in Sect. 4. Fasteners are identified by mass, size, and position.

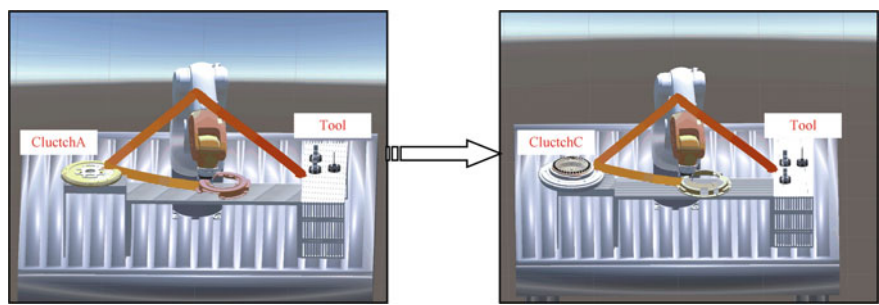


Fig. 8 Disassembly process model update from Clutch A to Clutch C

Table 3 Test case for implementing CDT

Product type	Clutch A		Clutch B		Clutch C	
	Before	After	Before	After	Before	After
Components identification	4	4	4	4	4	4
Correct component identification	1	4	1	4	2	4
Fasteners identification	6	6	6	6	9	9
Correct fastener identification	2	6	2	6	0	6
Disassembly sequence instance	8	8	8	8	10	10
Correct disassembly sequence	0	8	0	6	0	6
User correction required	8	0	8	2	10	4
Total instances	18	18	18	18	23	23
Correct instances	3	18	3	16	2	16
Success rate	16.7%	100%	16.7%	88.9%	8.7%	69.5%

Fasteners identification in the table means the number of identifications in Clutches A, B, and C. The disassembly sequence represents the individual disassembly sequence of all fasteners and associated components. The disassembly sequence represents the individual disassembly sequence of all fasteners and associated components.

The total instances include total component identifications, total fastener identifications, and disassembly sequence instances in each clutch. These three types of instances represent the success rate of combined product parts and product disassembly. Because the fastener configuration of Clutch C is different from Clutches A and B, there are only 2 correct instances out of 23 in total instances (a success rate of 8.7%). After ten simulation runs in CDT and ontology updates, the number of correct instances was raised to 16 (a success rate of 69.5%). As reported in the results, the majority of components and fasteners involved in the robotic disassembly process were not able to be identified by the system prior to the execution of CDT. Subsequent to the execution of CDT, it effectively recognized most of the fasteners and component types through the inferences made by the ontological structure of the cognitive model. However, due to the relative disconnection between fasteners in Clutch C's cover and those in C7–C9, successful identification could not be achieved during the disassembly process.

6 Conclusion

The proposed CDT model of robotic disassembly process enables geometric, physical, behavior, and rule model update for clutch-type product disassembly. During the disassembly process, it has cognitive capability to gradually infer the main disassembly features and relationships of a product or components and applies them to new products through gaining experience. Its cognitive capability is achieved by expanding the classes of ontologies, SWRL rules, object properties, and disassembling instances. In the meantime, these are used as new knowledge for robot disassembly system development. Although the test was conducted with the disassembly of the clutch, and only the disassembly process of the fasteners and the clutch cover was considered, there are still more uncertainties of the products. Other uncertainties in the robotic disassembly process include changes in product structure, changes in disassembly conditions, missing parts, and changes in location of components.

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Digital Twin-Based Energy-Efficient Trajectory Optimization for Robotic Pick-and-Place Process Under Uncertain Payload



Wen Yao, Wenjun Xu, Jiayi Liu, Hang Yang, and Zude Zhou

Abstract Robotic pick-and-place process is a typical robotic manufacturing process, which is widely used in many applications. In the meanwhile, sustainable manufacturing is being paid much attention and the energy consumption during the robotic pick-and-place process could be further improved to enhance the sustainability. However, the payload deployed on the industrial robot is always uncertain and the existing energy-efficient trajectory optimization method could not be dynamically used for this situation. In this paper, digital twin-based energy-efficient trajectory optimization for robotic pick-and-place process under uncertain load is proposed. The digital twin for robotic pick-and-place process under uncertain payload is firstly built. Afterwards, the proximal policy optimization algorithm is used to realize energy-efficient trajectory optimization under uncertain payload. Finally, case study is conducted to validate the proposed method. The results show the effectiveness of the digital twin model and the Proximal Policy Optimization algorithm in reducing the energy consumption of the robotic pick-and-place process, which improves the sustainability of robotic pick-and-place process.

Keywords Energy-efficient trajectory · Uncertain payload · Digital twin · Pick-and-Place process

1 Introduction

In recent years, robotic pick-and-place process has been widely used in manufacturing process due to its high efficiency. According to the China Energy Statistical Yearbook, total energy consumption increased from 4719.2 Mtce in 2018 to 5410.0

W. Yao (✉) · W. Xu · J. Liu · H. Yang · Z. Zhou
School of Information Engineering, Wuhan University of Technology, Wuhan 430070, China
e-mail: yw@whut.edu.cn

W. Yao · W. Xu · J. Liu · H. Yang
Hubei Key Laboratory of Broadband Wireless Communication and Sensor Networks, Wuhan University of Technology, Wuhan 430070, China

Mtce in 2022, with industrial production accounting for about 66.8% of the total. Sustainable manufacturing is the creation of products through economic production processes that conserve energy and natural resources while minimizing negative impacts on the environment. The energy efficiency during robotic pick-and-place process could be further optimized to enhance the sustainability of manufacturing process.

For the optimization of energy efficiency in the robotic pick-and-place process, research showed that optimizing the robotic trajectory has great potential for energy efficiency [1]. Research conducted that increasing the mass applied to the robot causes an increase in energy consumption [2]. During robotic pick-and-place process with uncertain payload, the mass of the product is directly related to its operating energy consumption. However, existing energy-efficient optimization studies are designed with the assumption that the payload is known. The optimal energy-efficient trajectory of the robot needs to be dynamically adjusted according to the mass of the product when the payload is uncertain during robotic pick-and-place process.

The digital twin (DT) modeling is the core for accurate portrayal of the physical entity. Driven by data and model, the DT can perform monitoring, simulation, prediction, optimization, and so on [3]. In this paper, DT technology is used to solve the energy-efficient optimization problem of robotic pick-and-place process under uncertain payloads. The DT model is a mirror reflection of the physical object or process [4]. In the case of uncertain payloads during robotic pick-and-place process, the payload data could be monitored by sensors in real-time. The connection and continuous interaction between the physical entity and the DT can make the DT respond to the dynamic changes of the physical entity [4]. After sensing the mass of the payload, the data is transmitted to the DT, where it is dynamically planned to generate the optimal energy-efficient trajectory under the perceived payload. The novelty of this paper is to build a DT of robotic pick-and-place process and solve the uncertain payloads problem through the data interaction module, utilizing the Proximal Policy Optimization (PPO) algorithm to dynamically optimize the energy efficiency of robotic pick-and-place process according to the perceived payload.

The rest of this paper is organized as follows: Sect. 2 provides a review of related works on robotic energy efficiency and DT technology; Sect. 3 introduces the framework of the proposed method; Sect. 4 describes the DT model of robotic pick-and-place process; Sect. 5 describes the energy-efficient trajectory optimization by using PPO algorithm; Case study and the results are given in Sect. 6; Sect. 7 summarizes this paper and discusses the future work.

2 Related Works

Analyzing the influencing factors of robotic energy efficiency is essential for energy-efficient optimization. Existing research analyzed the quantitative relations between adjustable motion parameters and energy consumption, such as joint angle, joint

velocity, joint acceleration, and motion time, by using neural networks and simulation environments [5, 6]. In addition, studies showed that the robotic payload has an influence on energy consumption [2, 7]. Establishing a computational model of robotic energy consumption is a prerequisite for energy-efficient optimization. Traditional research methods parameterize the robot joint position, acceleration, and motion time to help establish the energy consumption model [8, 9]. In order to accelerate model reconstruction and improve the energy consumption modeling accuracy on small-scale datasets, Yan et al. proposed a transfer learning-based approach for modeling energy consumption [10]. In terms of improving robotic energy efficiency, Riazi et al. presented four different cost functions and a multi-objective optimization to minimize energy consumption and peak power of robots [11]. Different optimization methods such as polynomial interpolation, and genetic algorithm (GA) are used to optimize the adjustable parameters for energy-efficient optimization [5, 12, 13].

The concept of DT was presented by Grieves and Vickers [14]. The DT is in a period of rapid development in recent years. Tao et al. proposed a 5-dimension DT model, stating that DT modeling includes geometric, physical, behavioral, and rule models [15]. Many studies have combined DT technology with robots. Constructing the DT space of the robot, the interaction of virtual and real data helped to reduce the motion error of the physical entity [16–18]. Teng et al. discussed the challenge and promising future for the development of a DT-based energy-saving system in the industry [19]. Some studies proposed DT-based energy modeling methods for energy consumption simulation and prediction [20, 21]. Chen et al. established a computer numerical machine tool model based on DT; the Particle Swarm Optimization (PSO) algorithm is introduced to optimize milling parameters for improving energy efficiency [22].

From the above literature, current research on energy-efficient optimization mainly focuses on optimizing the motion parameters, by establishing a mathematical model of robotic energy efficiency and using optimization algorithms, with the assumption that the robotic payload is known. DT-based energy efficiency studies mainly focus on modeling and prediction, without considering the energy-efficient optimization of robotic pick-and-place process under uncertain payload. Therefore, this paper builds a DT model of robotic pick-and-place process, the data interaction module of the DT is used to solve the uncertain payload problem. The PPO algorithm is used to optimize the energy efficiency of robotic pick-and-place process.

3 Framework

This section describes the framework of DT-based energy-efficient optimization, as shown in Fig. 1. It consists of the physical robotic pick-and-place process, its DT model, the data interaction module, and the energy-efficient optimization module.

The physical robotic pick-and-place process consists of a 6-axis robot, a six-dimensional force sensor, a gripper, and unknown mass products. The six-dimensional force sensor is mounted with the gripper at the end of the robot.

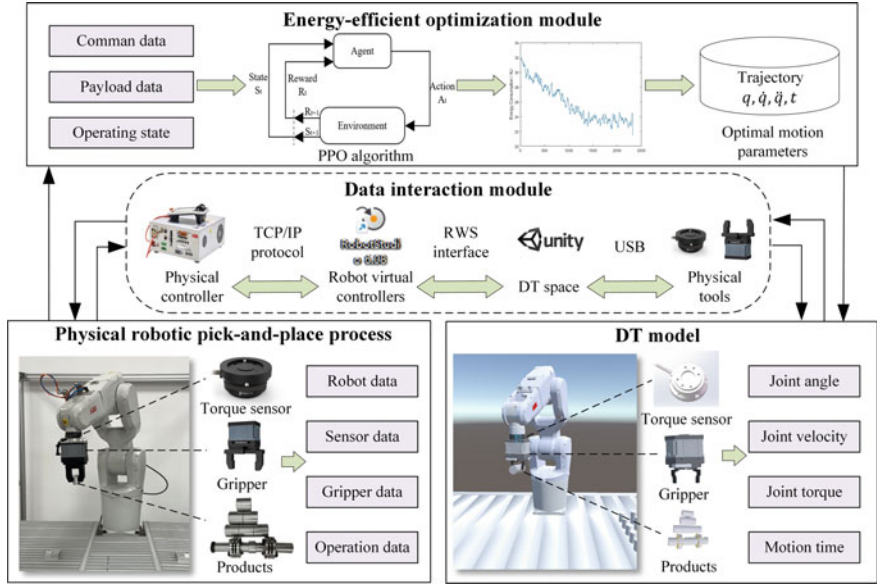


Fig. 1 DT-based energy-efficient optimization framework

After gravity compensation, the uncertain payload on the gripper could be measured accurately by the six-dimensional force sensor during the pick-and-place process.

The DT model is a digital reflection of the physical process, which is described from four dimensions: geometric model, physical model, behavioral model, and rule model. Four-dimensional models are integrated and imported into Unity3D to form the digitalization and visualization of the DT model.

The data interaction module is the communication channel between the physical robotic pick-and-place and its DT model. The Robot Studio in PC establishes socket communication with the physical robot based on the TCP/IP protocol. The Robot Web Service (RWS) interface based on the HTTP protocol provides client–server communication between the DT in Unity3D and Robot Studio. The six-dimensional force sensor is connected to DT space via USB to read the real-time payload data.

Based on DT, the optimal energy-efficient trajectory planning for robotic pick-and-place process under uncertain payload is realized in the energy-efficient optimization module by using PPO algorithm. The real-time sensing data and the pick-and-place task demand data are transferred to the trained PPO model, which dynamically generates the optimal trajectory. Finally, the optimal energy-efficient pick-and-place process motion parameters are transmitted to the DT for simulation and verification.

4 DT Model of Robotic Pick-and-Place Process

The DT model of robotic pick-and-place process consists of the geometric model, the physical model, the behavioral model, and the rule model.

4.1 Geometric Model

The geometric model describes the size, structure, spatial position, and attitude of robotic pick-and-place process. SolidWorks is used to construct the 3D structure and form the mesh files, including the robot, the gripper, a six-dimensional force sensor, and products. The mesh files are imported into Unity 3D to visualize the geometric model. Anchor the geometric position of each module in Unity 3D to be consistent with the physical entity. Besides, export the URDF file of the robot, the sensor, and the gripper separately from SolidWorks. Add the relative spatial position of the sensor and the gripper to the robotic URDF file. Finally, import URDF files into Unity3D.

4.2 Physical Model

The physical model describes the physical properties of robotic pick-and-place process. The inertia parameters and collision properties of each model are added in the URDF file. In addition, the kinematic model and the dynamics model are constructed in Unity3D. The kinematics calculation of the robot is implemented through the Final IK plugin. The dynamic model is constructed in PyCharm using the Peter Corke's robotic toolbox plugin [23]. The joint velocity is calculated as (1), where $\dot{q}$ is the joint velocity; J is the Jacobi matrix of the robot; $\dot{x}$ represents the end-effector velocity.

$$\dot{q} = J^{-1}\dot{x} \quad (1)$$

The dynamic model can be described as (2):

$$\begin{aligned} \tau = & M(q)\ddot{q} + (I_n \otimes \dot{q}^T) \begin{bmatrix} C_1(q) \\ \vdots \\ C_n(q) \end{bmatrix} \dot{q} + \left(F_c \begin{bmatrix} \text{sgn}(\dot{q}^1) \\ \vdots \\ \text{sgn}(\dot{q}^n) \end{bmatrix} + F_v \dot{q} \right) \\ & + G(q) + \begin{bmatrix} J_1(q) \\ J_2(q) \end{bmatrix}^T \left(\begin{bmatrix} m\ddot{x} \\ \Gamma\dot{\omega} + \omega \times \Gamma\omega \end{bmatrix} + \begin{bmatrix} mg \\ O \end{bmatrix} \right) \end{aligned} \quad (2)$$

where M is the inertia matrix; q is the joint position; $\ddot{q}$ is the joint acceleration; C is the Coriolis force and centrifugal force; F_v and F_c are diagonal matrix, the diagonal elements represent the Coulomb friction coefficient and viscous damping coefficient of the corresponding joint; G is the gravity vector; The last term in (2) represents the equivalent joint torque caused by the inertial and gravitational forces of the payload during robotic pick-and-place process; m and Γ are the mass matrix and inertia matrix of the payload. O is the zero vector. Therefore, the total instantaneous power of the robot is given by (3):

$$P_{out} = \sum_{i=1}^6 \tau_i \dot{q}_i \quad (3)$$

The mechanical energy of the robot is shown in (4).

$$W_t = \int_0^t P_{out} dt. \quad (4)$$

4.3 Behavioral Model

The behavioral model is constructed to control the specific behavior of the DT model, as shown in Fig. 2, including (a) moving to the position of the product to be picked up; (b) closing the gripper and picking product; (c) gripping product to the target position; (d) opening the gripper and placing product. This paper uses the parent-child object relationship mechanism and writes the corresponding C# control scripts in Unity3D to build the behavioral model.

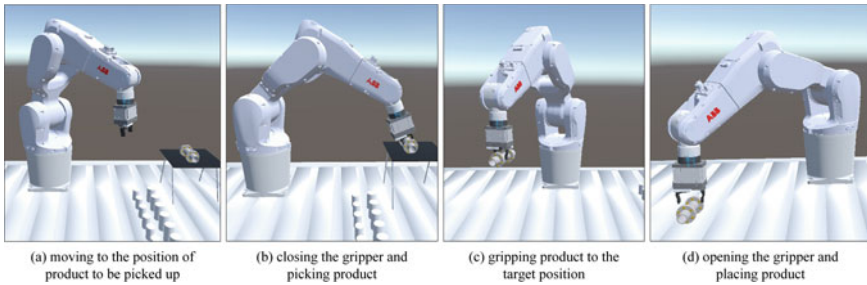


Fig. 2 Behavioral model

4.4 Rule Model

The rule model consists of robot workspace constraints, kinematic constraints (velocity constraints, acceleration constraints, collision constraints), dynamic constraints (torque constraints), and energy consumption rule. The DT rule model is constructed by modeling and analyzing the correlation between the velocity, acceleration, torque changes and energy consumption of robotic pick-and-place process.

5 Energy-Efficient Optimization by Using PPO

5.1 PPO Algorithm

The PPO is a policy-based reinforcement learning algorithm, which follows the Actor-Critic architecture, as shown in Fig. 3. The PPO algorithm has two major variants: PPO-penalty and PPO-clip. The PPO-clip is used in this paper to implement the gradient update.

PPO-clip introduces important sampling in the model update, using two policies with parameters θ and θ_{old} . Where $\pi_{\theta_{old}}$ samples data in the interaction with the environment. Important sampling evaluates the quality of the model update by calculating the ratio of the old policy $\pi_{\theta_{old}}$ to the new policy π_{θ} , as shown in (5).

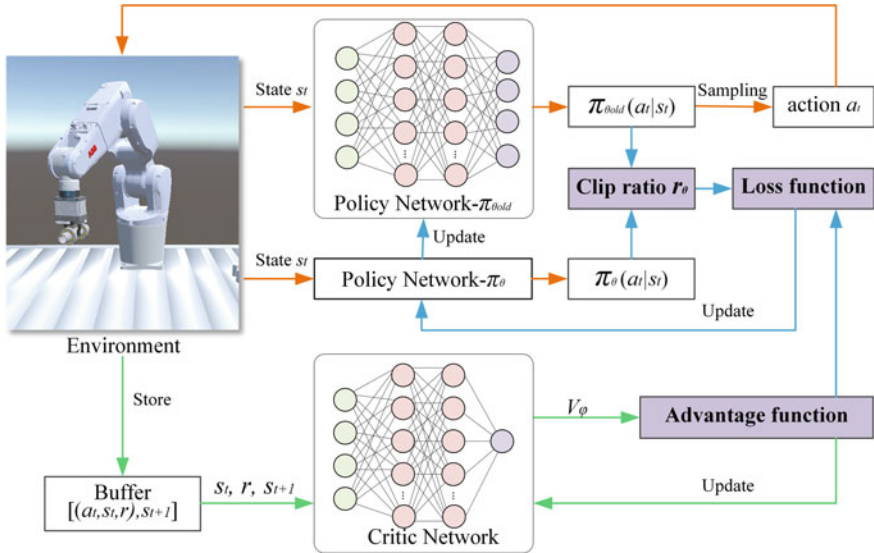


Fig. 3 Framework of the PPO algorithm

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \quad (5)$$

The objective function is shown in (6). The loss value is back-propagated into the new policy network π_θ for gradient updating. Finally, the network weights of the new policy network are used to update the old policy network.

$$L^{CLIP}(\theta) = \hat{E}_t \left[\min \left(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \varepsilon, 1 + \varepsilon) \hat{A}_t \right) \right] \quad (6)$$

where ε is a hyperparameter representing the clip function ratio; $\hat{A}_t$ is the advantage function indicating the advantage of taking action a_t over taking other actions in state s_t , which is calculated by generalized advantage estimation (GAE), as shown in (7).

$$\hat{A}_t = \delta_t + (\gamma\lambda)\delta_{t+1} + \dots + (\gamma\lambda)^{T-t+1}\delta_{T-1} \quad (7)$$

where λ and γ are the discount factors; $\delta_t = r_t + \gamma V_\varphi(s_{t+1}) - V_\varphi(s_t)$ is the temporal difference (TD) error, used for the adjustment of the policy and the value estimator; V_φ denotes the value-function approximated by the critic network. The critic network is updated by minimizing the loss function, as shown in (8).

$$L(\varphi) = E[(V_\varphi(s_t) - \hat{R}(s_t))] \quad (8)$$

To avoid the new policy π_θ being too far away from the old policy $\pi_{\theta_{old}}$ during the training process, Kullback–Leibler (KL) divergence is introduced in PPO to stop updating the policy early. KL divergence is used to calculate the divergence between two probability distributions, as shown in (9).

$$d_{KL}(\pi_{\theta_{old}} || \pi_\theta) = \log \left(\frac{\pi_{\theta_{old}}(a_t|s_t)}{\pi_\theta(a_t|s_t)} \right). \quad (9)$$

5.2 Environment Setup of PPO

The energy-efficient optimization of robotic pick-and-place process can be expressed as a typical Markov Decision Process (MDP) consisting of $\langle S, A, R, P, \gamma \rangle$, where S and A represent the continuous state space and continuous action space of the environment, t respectively; R is the reward function; P is the state transition probability function; γ is the discounting factor of the future reward. The specific definition can be expressed as follows:

$$s_t = (o_{xt}, o_{yt}, o_{zt}; W_t), s_t \in S \quad (10)$$

$$a_t = (p_{xt}, p_{yt}, p_{zt}; t), a_t \in A \quad (11)$$

$$s_{t+1} \sim P(s_{t+1}|s_t, a_t) \quad (12)$$

The action space consists of the robot end-effector position p_t and the motion time t of the next step. The state space consists of the pick-and-place process target position o_t and the real-time energy consumption W_t of the pick-and-place process. The agent samples action according to current state s_t . The joint position, velocity, and acceleration of the robot are derived from the inverse kinematics calculation. Then, calculate the joint torque and the energy consumption of state s_t through the constructed physical model. When the environment finishes executing action a_t , the next state s_{t+1} and the reward r_t are given back to the agent. The reward consists of distance reward r_{dist} , energy-efficient reward r_{w_t} and termination reward r_{Δ} .

The distance is the Euclidean distance between the robot end-effector and the target position during robotic pick-and-place process. The closer the distance, the reward should be larger. Therefore, the reciprocal of the Euclidean distance is used as the distance reward ($d_t = 1/D_t$), which is normalized here, as shown in (13).

$$r_{dist} = \frac{d_t - d_{min}}{d_{max} - d_{min}} \quad (13)$$

The energy-efficient reward is the robotic cumulative energy consumption in state s_t , which is calculated by (14). The higher the energy consumption, the reward should be smaller. Therefore, the reciprocal of the energy consumption is the energy-efficient reward ($w_t = 1/W_t$).

$$r_{w_t} = \frac{w_t - w_{min}}{w_{max} - w_{min}} \quad (14)$$

Considering the constructed rule model, if the action exceeds the robotic workspace or the training reaches the maximum episode length (max_ep_len) allowed, but robotic pick-and-place process does not reach the target position, the training of the current trajectory should be terminated and given a penalty. A positive reward is given if robotic pick-and-place process reaches the target position and the energy efficiency is the best in history. Therefore, the termination reward r_{Δ} is given by (15).

$$r_{\Delta} = \begin{cases} -1, & \text{out of workspace or } max\_ep\_len \\ 0.5, & D_t < 0.01 \text{ and } W == W_{min} \\ 0 & \text{others} \end{cases} \quad (15)$$

The reward function r_t can be expressed by (16).

$$r_t = r_{dist} + r_{w_t} + r_{\Delta}. \quad (16)$$

6 Case Study

In this section, the energy-efficient optimization based on PPO is verified by simulation in the DT space. Robotic pick-and-place process consists of the ABB IRB 1200-7.0 industrial robot, the Robotiq FT300 force/torque sensor, the DH PGI-140-80 gripper, and different products. The experiment assumes that the payload has been measured by the sensor of the physical pick-and-place process, and transmitted to the DT for energy-efficient optimization. The energy-efficient optimization performance of the PPO is evaluated by setting up four groups of experiments with different payloads, 0.5, 1, 2.5, and 5 kg.

The training parameters of the PPO are set as shown in Table 1. The robotic motion time is limited to 0.2–0.5s per step. And the displacement of the robot does not exceed 0.1 m per step. Therefore, each step can be considered as a uniform motion. Then, the joint angle, velocity, and acceleration of the robot are derived from the inverse kinematics calculation. Finally, the cumulative energy consumption at state s_t is calculated by (4).

The cumulative reward and energy consumption during the PPO training process is shown in Fig. 4, verifying the effectiveness of the PPO in optimizing energy efficiency of robotic pick-and-place process. In the initial period of training, the agent selected actions randomly, resulting in large variations in reward. The PPO converges after about 80 epochs. And the energy efficiency of the pick-and-place process under different payloads tends to converge after about 100 epochs. During the training process, the agent needs to learn the target location of the pick-and-place task and reduce energy consumption. Therefore, the agent needs a longer interaction to reach the energy efficiency convergence than the reward convergence. Increasing the end-effector payload leads to an increase in energy consumption of robotic pick-and-place process. The optimized average energy consumption of robotic pick-and-place process is 806 J for a 0.5 kg payload, 872 J for 1 kg, 1048 J for 2.5 kg, and 1215 J for 5 kg.

To further evaluate the performance of PPO, a comparison is made with the conventional GA and PSO. The population and the iteration number of GA and PSO are 15 and 150, respectively. The initial crossover probability of GA is 0.6,

Table 1 PPO algorithm parameters

Parameter	Value
Epoch	150
Gamma- γ	0.99
Lambda- λ	0.98
Clip ratio- ϵ	0.2
KL-threshold	0.02
Max_ep_len	1000
Activation function	Tanh
Network hidden layers	[128,128]

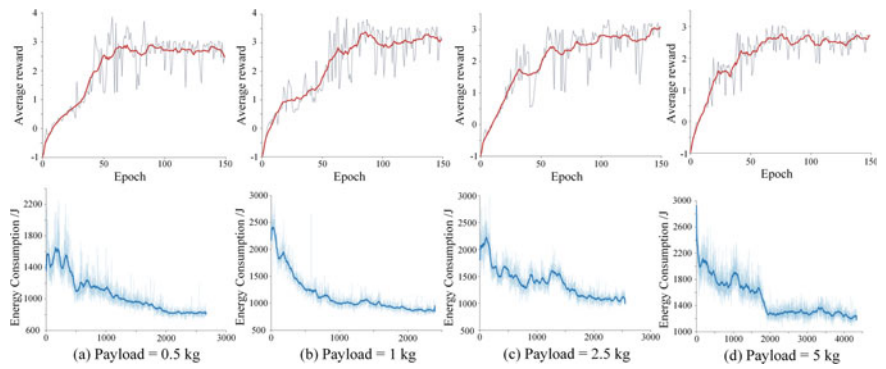


Fig. 4 The cumulative reward and the energy consumption during the training process

and the mutation probability is 0.07. The learning rates of PSO are: $c1 = 2$, $c2 = 2$, and the initial weight is 0.9. The performance of different algorithms for the optimal energy efficiency under different payloads is compared in Table 2. The results show that the optimal energy efficiency of robotic pick-and-place process based on the PPO is similar to that of GA, which is approximately 3–7% lower than PSO.

The average motion time for the pick-and-place process under different payloads is compared in Fig. 5. Apparently, The PPO-based has the shortest motion time for robotic pick-and-place process, which is about 30% faster than the PSO-based and 19% faster than the GA-based.

The running time of PPO, GA, and PSO is shown in Table 3. The GA and PSO take more time to iterate 150 generations due to the high time cost of calculating the robot joint configuration and energy consumption. In comparison, the PPO takes only about 1/4 of the time to find the optimal energy-efficient motion parameters.

Table 2 The optimal energy efficiency of PPO, GA, and PSO

	0.5 kg	1 kg	2.5 kg	5 kg
PPO	764.1 J	817.9 J	891.1 J	1071.0 J
GA	775.2 J	817.5 J	895.5 J	1061.2 J
PSO	798.7 J	845.6 J	933.0 J	1126.6 J

Fig. 5 Comparison of the motion time

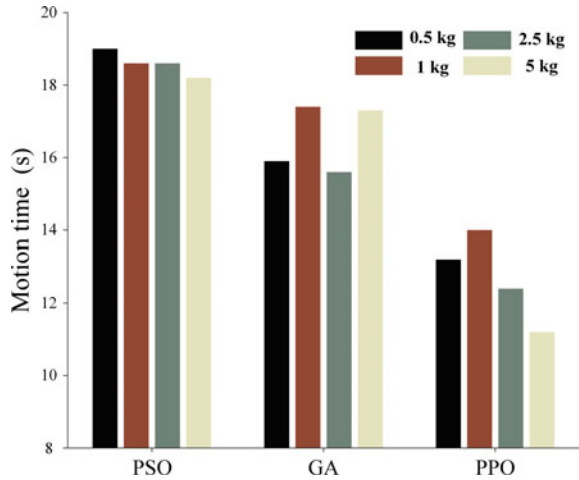


Table 3 Comparison of training time

Algorithm	Training time (h)
GA	2.36
PSO	1.99
PPO	0.56

When the payload is 1.5 kg, the motion parameters of the optimal energy-efficient pick-and-place process based on PPO are deployed in the DT space. The motion path of robotic pick-and-place process in DT space and its joint angle are shown in Fig. 6.

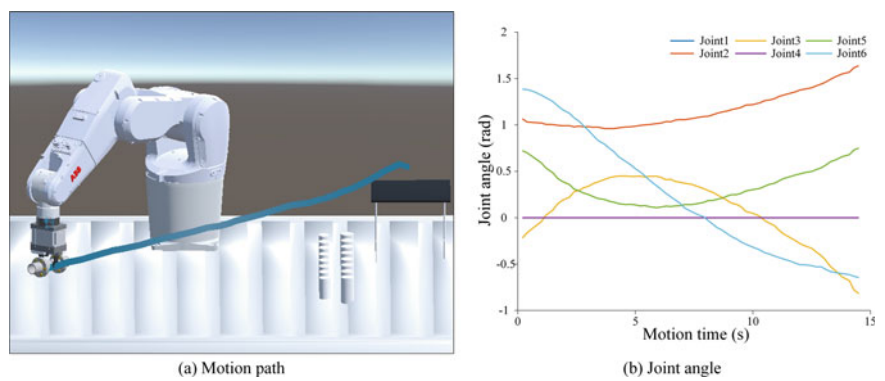


Fig. 6 Robotic pick-and-place process in DT space

7 Conclusion

In this paper, considering the uncertain payload of robotic pick-and-place process, DT is used to solve the energy-efficient optimization problem. First, the DT of robotic pick-and-place process is built. Then, the PPO is used to optimize the energy efficiency of robotic pick-and-place process. Finally, case studies are conducted to demonstrate the effectiveness of the proposed method. Future work will further improve the energy-efficient optimization method. The simulation results of the DT will be applied to the physical robot pick-and-place process to evaluate the effectiveness of the proposed method.

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OPC UA Discovery-Driven Dynamic Reconfiguration of Robotic Manufacturing Systems: Method and Deployment



Zhijian Yang, Xun Ye, Ruifang Li, and Wenjun Xu

Abstract In recent years, the diversification and individuation of market demand are becoming more and more obvious, which puts forward higher requirements for the flexibility of the manufacturing system. For cyber-physical systems, flexibility refers to the ability to be scalable and reconfigurable. The traditional industrial reconfiguration method is inefficient and lacks practical deployment, it can no longer achieve the flexibility required in practical manufacturing processes. To address these problems, this paper proposes a reconfiguration solution based on an optimization algorithm and the OPC UA discovery mechanism. The optimization algorithm is used to fast generate the optimal combination of system resources for minimizing the makespan. OPC UA discovery enables the plug-and-produce functionality that can accelerate new device integration. The proposed solution can provide decision-making support for the rapid reconfiguration of the manufacturing system and also allow for the dynamic integration of newly inserted devices into the manufacturing system. Finally, the feasibility of the solution is verified by a demonstration of reconfiguration in robotic manufacturing systems.

Keywords OPC UA discovery · Reconfiguration · Information model · Data communication · Local discovery server

1 Introduction

Industry 4.0 has led to significant advancements in the digitization of the manufacturing industry [1]. This has resulted in dramatic changes in the industrial scene due to the rapid progress in technology and the rise in demand [2]. Consequently, the manufacturing industry is expected to become more flexible, which in turn, requires the

Z. Yang · X. Ye (✉) · R. Li · W. Xu

School of Information Engineering, Wuhan University of Technology, Wuhan 430070, China
e-mail: yexun1024@whut.edu.cn

Hubei Key Laboratory of Broadband Wireless Communication and Sensor Networks, Wuhan University of Technology, Wuhan 430070, China

incorporation of a greater variety of devices in industrial architectures. The increased use of such devices sets a higher demand for manufacturing system flexibility. In the context of cyber-physical systems, flexibility is defined as the ability to be both scalable and reconfigurable. A reconfiguration is a vital approach to achieving the flexible production of manufacturing systems. This process involves the reorganization of production resources, which can be done by updating the devices, production processes, and so on.

A reasonable reconfiguration solution can not only improve the reconfiguration efficiency of the manufacturing system but also reduce the production cost [3]. Facing the changing market demand, traditional industrial manufacturing can no longer meet the requirements of flexibility. Thus, the reconfiguration of the manufacturing system is necessary. Existing research has focused on two areas: reconfiguration methods for manufacturing systems, and the technical implementation of reconfiguration. In reconfiguration studies of manufacturing systems, optimization algorithms are often used to solve the combination of system resources. By combining flexible job scenarios and focusing on makespan minimization, the algorithm can obtain the optimal resource combination. However, little of the existing research on reconfiguration has focused on deploying methods into manufacturing systems.

In the implementation of reconfiguration, to improve the reconfiguration efficiency in manufacturing systems, the overhead of configuring the newly added devices should be as small as possible. When a device is added, it should be automatically detected and configured. Existing researches use Open Platform Communications United Architecture (OPC UA) discovery to enable automated device discovery capabilities, simplifying the integration of new devices. OPC UA discovery is a technology that facilitates device configuration. The discovery process defines how the OPC UA client finds the OPC UA server in the network and establishes a connection with the server. OPC UA discovery includes a general discovery process, local discovery server (LDS), and global discovery server (GDS). LDS can track all OPC UA servers on the same host. The contribution of this paper: (1) Use genetic algorithms to fast generate optimal resource allocation. (2) Utilize OPC UA to enable automatic device discovery that accelerates device integration. (3) Propose a control architecture that combines resource allocation and automated device discovery. (4) Verify the feasibility of the solution using a robotic manufacturing system.

The rest of the paper is organized as follows. Section 2 gives the current status of research on reconfiguration. Section 3 describes the proposed LDS-based dynamic reconfiguration solution. Section 4 verifies the reconfiguration solution with a robotic manufacturing system. This paper ends with Section 5 which gives the conclusion and future works.

2 Related Works

In terms of reconfiguration methods for manufacturing systems, existing researches mainly use optimization algorithms to solve the combination scheme of the system's resources. Bi et al. [4] emphasized that Reconfigurable Manufacturing Systems (RMS) are pivotal in enabling large-scale customization. Unlike integrated systems, RMS can provide system configurations that satisfy diverse functional requirements. In their study, they proposed a methodology for designing RMS that can be extrapolated to RMS with analogous characteristics. Chaube et al. [5] introduced a methodology for producing dynamic process plans for RMS, leveraging an adapted nondominated sorting genetic algorithm II (NSGA-II) algorithm to improve both manufacturing cost and time. Goyal et al. [6] presented an approach to optimize RMS in several areas, such as machine utilization. The methodology was formulated based on the NSGA-II. Liu et al. [7] proposed an algorithm for resource allocation that enhances the efficient utilization of device resources. Musharavati et al. [8] devised an enhanced simulated-annealing algorithm to solve the process planning in RMS. Kumar et al. [9] employed the Multi-objective Self-Organizing Migrating Algorithm to achieve an optimal solution. Yuan et al. [10] devised a reconfiguration model in the context of cloud manufacturing environments. The model employs an improved memetic algorithm that provides maximum productivity. Maniraj et al. [11] utilized an ant colony optimization approach to configuring RMS. Touzout et al. [12] proposed an iterative multi-objective integer linear programming approach. This approach takes into consideration the production costs, duration of production, and greenhouse gas emissions of the manufacturing process.

In terms of the integration of field devices, Zheng et al. [13] presented a method for modeling the ontology of manufacturing resources, which takes into account the unique characteristics of RMS. Wan et al. [14] proposed a resource utilization-based approach for reconfiguration. This approach uses web ontology language to construct a manufacturing resources ontology and map manufacturing resources onto model instances. Wang et al. [15] proposed an interoperable architecture for the Industrial Internet of Things that enhances interoperability and reduces the latency in traditional manufacturing systems. The architecture is based on OPC UA and Software-Defined Networking technologies. Jirkovsky et al. [16] analyzed the issues related to device integration and suggested a solution that facilitates the rapid addition of devices to the manufacturing system. The solution leverages the benefits of OPC UA and Semantic Web technologies. Kadera et al. [17] demonstrate the potential of integrating Cyber-Physical Systems and Semantic Web technologies. They developed a prototype called Semantic Big Data Historian to achieve plug-and-produce (PnP). Ye et al. [18, 19] proposed a three-tier architecture based on Asset Administration Shell (AAS) to enable PnP for manufacturing devices. Additionally, they developed a cloud-enabled AAS solution for implementing cyber-physical manufacturing. Profanter et al. [20] propose a multi-tier system architecture to support PnP functionality. They implement this architecture based on OPC UA.

Most of the studies have focused on achieving the optimal method through optimization algorithms. But the deployment of the method has rarely been considered. Although the emergence of PnP provides a direction for deployment, there is a lack of research on deployment at the whole system level. Considering that the genetic algorithm is simple to operate and can solve the optimal method quickly [21] and OPC UA Discovery can accelerate the integration of devices, a solution based on both is proposed in this paper.

3 Dynamic Reconfiguration Solution

3.1 Dynamic Reconfiguration Architecture

The reconfiguration architecture of the manufacturing system based on OPC UA discovery is shown in Fig. 1. The reconfiguration architecture mainly consists of the enterprise layer, the platform layer, and the device layer.

The device layer is the physical asset in the manufacturing system, consisting of 6-axis robots, fixture change systems for robots, ring conveyor lines, etc. The device layer is responsible for generating and collecting real-time operational data and status parameters and changing execution actions according to control commands. To ensure interconnectivity between the device layer and the other layers, each component has a separate OPC UA server. Data communication with the upper layer is done by the server.

The platform layer acts as middleware and is responsible for connecting the enterprise layer and the device layer. The data information of the devices is integrated here; the control commands from the enterprise layer are received and forwarded here. In this paper, the platform layer is built by OPC UA local discovery server. The information model is stored in this layer. The platform layer holds the registration information of physical assets, which can be used to detect the device status and respond to new devices.

The enterprise layer implements decision-making functions and the visualization of data and utilizes optimization algorithms to generate the best resource combination solution for the system. Through the OPC UA client, the enterprise layer can read the data information in the device layer and also generate control policies to manage the device layer. The data of the physical entities collected in the device layer are transferred to the database via the OPC UA protocol for real-time storage.

3.2 Information Model

The information model provides essential information and knowledge about all field devices, including device status, control data, monitoring data, and fault, or alarm

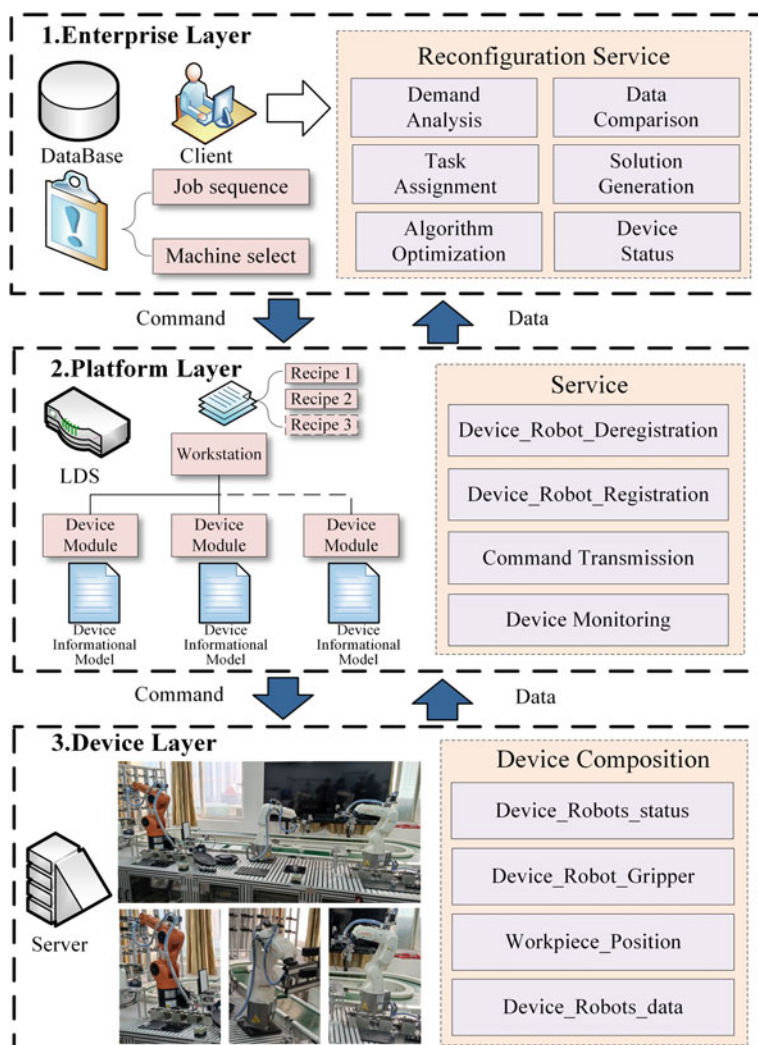
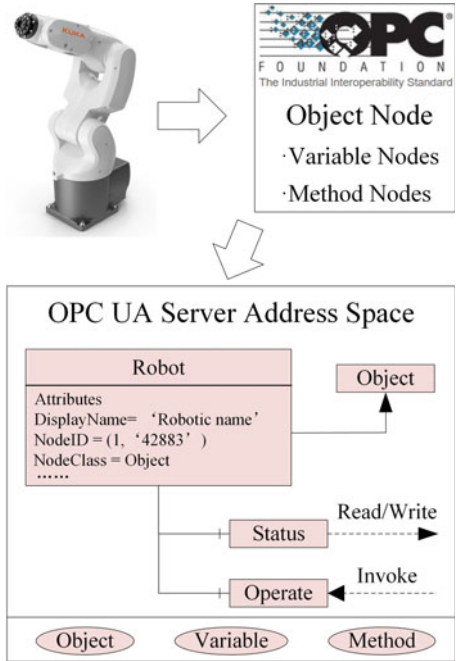


Fig. 1 Reconfigured architecture of robotic manufacturing systems

data. One main advantage of OPC UA is its ability to describe the information model accurately. By defining device objects, attribute variables, and operation methods to organize data, an information model can be established for the device. Figure 2 shows the structure of the OPC UA information model. Nodes depicting the device functions are divided into eight categories based on their purpose. The most critical categories include Object, Variable, and Method. Object nodes manage variables, methods, or other object nodes, while Variable nodes expose object data values read or written externally. Method nodes implement specific functions called upon by the

Fig. 2 OPC UA information model for robots



client, where the server returns the corresponding output after executing the required function.

OPC UA server abstracts entities into the information model in the address space. Once an OPC UA client and OPC UA server connection are established, external devices can call “Read”, “Write,” and “Browse” services to access the information model in a request-response manner.

3.3 Reconfiguration Process

In case the current system resources are insufficient to meet production requirements for a new order, the manufacturing system must be reconfigured. This can be achieved by updating the number and types of devices and adjusting the work-piece processes to better allocate the resources of the system. This paper employs a genetic algorithm to obtain the optimal combination of resources. The reconfiguration strategy can be obtained by comparing the device combination with the current device configuration. To achieve rapid deployment of reconfiguration policies, we need to complete the four phases of discovery, configuration, production, and reconfiguration. The above steps are marked with serial numbers in Fig. 3 and corresponding descriptions are elaborated in the following.

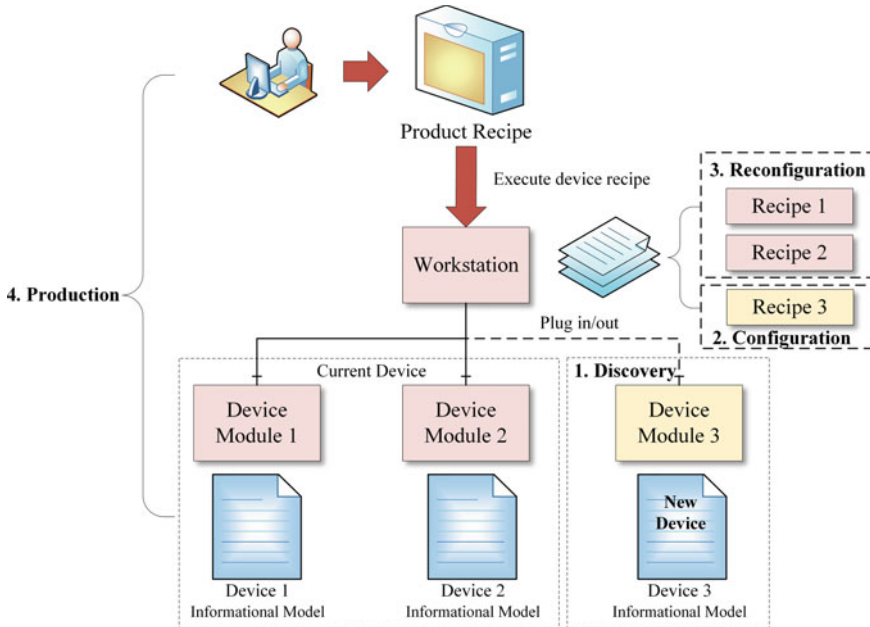


Fig. 3 Aggregation of device models

Discovery phase. Each device has an information model that follows the specification and provides information about its functionality. The information model realizes the mapping of devices from the physical world to the information world. When a new device (i.e., device module 3) is added to the system, the new device registers to the middleware. The task of the middleware is to keep track of all the devices available in the system. OPC UA is the ideal middleware to support the PnP concept. The plugging and unplugging of devices can be detected during the discovery phase.

Configuration phase. The goal of the configuration phase is to enable the new device in the system to perform manufacturing tasks. Skill is the realization of a specified capability on a specific resource. The execution of a skill depends on the recipe of the skill. Recipes for skills are executable instances that meet specific production requirements. Devices should be pre-configured to be able to perform product-specific tasks (i.e., recipe 3).

Reconfiguration phase. The goal of the reconfiguration is to enable the existing devices (i.e., device module 1 and device module 2) that can perform manufacturing tasks. Users can have the device perform new manufacturing tasks by editing existing recipes (i.e., recipe 1 and recipe 2). Whenever the system fails to meet the manufacturing needs, the corresponding device configuration should be implemented to make precise changes. In this manner, reconfiguration of the manufacturing system could be completed.

Production phase. The production phase consists mainly of the manufacture of the product. After the device gets all the necessary information, it starts triggering the execution of production tasks. The device plugged into the system will provide its skills. By performing the configured skills, the device can be manufactured for the specified function. Data from the production phase is transferred to the database through the protocol for real-time storage.

4 Case Study

This section introduces the implementation of the combination of genetic algorithm and automatic device discovery function. The whole experimental system is based on a three-tier architecture. In this section, we will show an example of the reconfiguration problem, the optimal resource allocation obtained by the genetic algorithm, the operation of rapid integration, and the method of constructing the whole system.

4.1 System Demonstration

The reconfiguration problem in this case study is described as follows. There are 3 workpieces, J_1 , J_2 , and J_3 , to be machined on 3 devices, KUKA KR3 R540 1 (R_1), KUKA KR3 R540 2 (R_2), and KUKA KR6 R700 (R_3); each workpiece contains one or more processes; the sequence of processes is predetermined; each process can be machined on different devices; the manufacturing time of the processes varies with the devices. The resources of the devices in the current manufacturing system are shown in Fig. 4. The leftmost device in the picture is R_3 , the middle device is R_1 and the rightmost device is R_2 .

As shown in Table 1, the new production order contains workpiece J_1 , workpiece J_2 , and workpiece J_3 , each of which has three processes. Workpiece J_1 has three processes: Process O_{11} , Process O_{12} and Process O_{13} . The first process O_{11} of workpiece J_1 can be machined on R_1 , R_2 and R_3 , where the machining time is two hours for R_1 , three hours for R_2 and eight hours for R_3 .

Table 2 shows the status information of the devices in the system. There are three device resources in the production line: R_1 , R_2 , and R_3 . In the current system, the configured devices are R_1 and R_2 . The new device is R_3 .

4.2 Generation of Reconstruction Strategy

The parameters of the genetic algorithm are: maximum number of evolutionary generations is 50, population size is 300, crossover probability is 0.8, and mutation probability is 0.3.



Fig. 4 Resources for devices in manufacturing systems

Table 1 Symbol and meaning

Workpiece	Process	KUKA KR3 R540 (R1)	KUKA KR3 R540 2 (R2)	KUKA KR6 R700 (R3)
J_1	O_{11}	2	3	8
	O_{12}	–	3	–
	O_{13}	1	–	20
	O_{21}	3	2	10
J_2	O_{22}	4	3	–
	O_{23}	–	4	–
	O_{31}	13	–	2
J_3	O_{32}	–	10	3
	O_{33}	5	–	16

Table 2 Status of the devices in the system

Device	Status	Registration
KUKA_KR3_R540 (R1)	Online	Registered
KUKA_KR3_R540 (R2)	Online	Registered
KUKA_KR6_R700 (R3)	Offline	Not registered

Figure 5 shows a Gantt chart of the processing corresponding to the most optimal individual. In the figure, device #1 represents R_1 , device #2 represents R_2 , device #3 represents R_3 . The first process of workpiece J_1 is manufactured in R_1 , the second process in R_2 , and the third process in R_3 . All three processes of workpiece J_2 are manufactured at R_2 . Workpiece J_3 is manufactured in R_3 for the first and second processes, and in R_1 for the third process. The devices required for the production of the order are R_1 , R_2 , and R_3 .

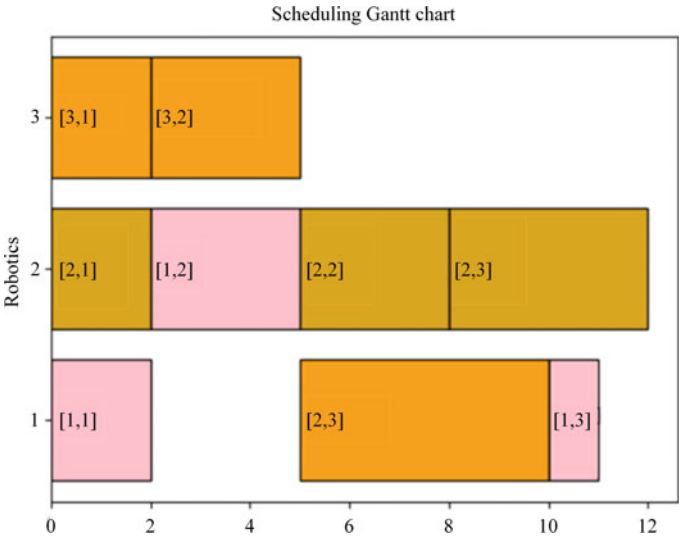


Fig. 5 Gantt chart of processing

4.3 Deployment

There is a unique information model consisting of various node objects, properties, and references in OPC UA, thus this paper chooses to use OPC UA to build the information model of the device. To implement plug-and-play in OPC UA, you must select a software stack that supports the discovery of service sets. Here we choose to use open62541 to build the platform for the project. Open62541 provides APIs for servers and clients, supports LDS services, and supports information models that can be automatically generated from XML files. Figure 6 provides the overall deployment diagram of the experimental system, which illustrates the composition of each layer and the communication protocol between adjacent layers.

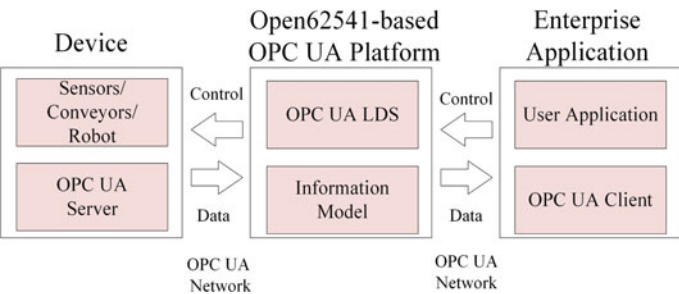


Fig. 6 Overall deployment framework of the experiment system

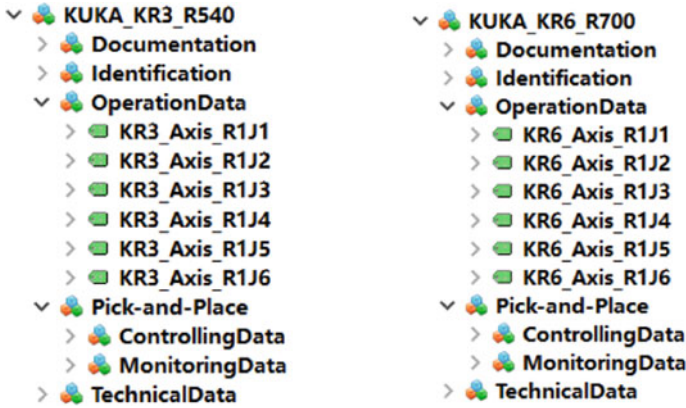


Fig. 7 The server of devices on the production line: The left side is the server of the existing devices in the system, and the right side is the server of the newly added device

In this paper, OPC UA server is used to host the information model and the relationship between nodes. The strategy identifies R_1 , R_2 , and R_3 as necessary devices for fulfilling the requirements. Accordingly, integrate R_3 into the manufacturing system in compliance with the policy. As can be seen from Table 2, R_3 is the new device. The server in the current system accessed by UaExpert is shown in Fig. 7. The left side is the server of the existing devices in the system, and the right side is the server of the newly added device.

Newly added devices can be integrated into the system through the discovery phase: Firstly, the necessary information is extracted from the newly added assets; Secondly, the data is organized by defining the object, attribute variable, and operation method of the device; Next, UaModeler is used to create the information model to realize the digital representation of KUKA KR6 R700; Finally, the new device added registers to the platform layer. Figure 8 illustrates the information model of the new device R_3 . Nodes are interconnected using HasComponent and HasProperty components defined in the OPC UA specification. HasComponent identifies the relationship and HasProperty identifies the properties of the node [22].

Through the configuration phase and reconfiguration phase, the device can perform specific manufacturing tasks. Before executing the skills, it is necessary to conduct a feasibility check to determine if the device can complete production based on the required parameters. Once a successful check has been carried out, the skills can be initiated by the OPC UA method. The field layer retrieves the corresponding control policy for the device from the OPC UA interface to update its status.

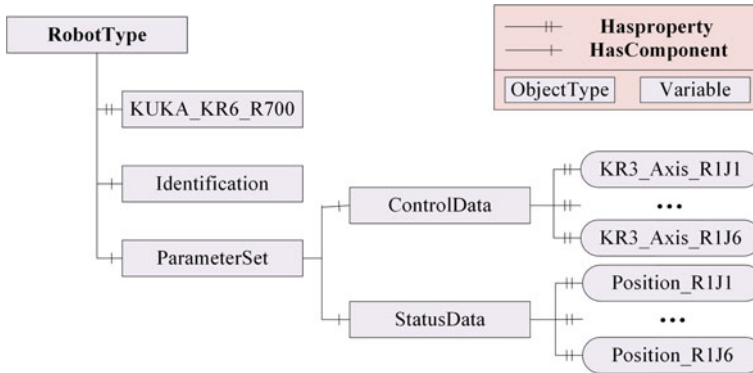


Fig. 8 The information model for a new device R3

5 Conclusion

In this paper, we investigate the development and implementation status of reconfiguration methods in manufacturing systems and argue for the necessity of a combination of both. The proposed solution ensures rapid reconfiguration of manufacturing systems and allows for swift integration of newly inserted devices into the manufacturing process. In the future, we intend to explore the integration of digital twin technology, which would allow for the virtual commissioning of reconfiguration strategy and real-time monitoring of field devices' status.

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Exploring in the Application Slicing Technology to Determine Spatial Information to Assist and Facilitate Robotic Disassembly



Kok Weng Ng, Hui Yin Chin, Mei Choo Ang, JianBang Liu, Ah-Lian Kor, and Meshal Iqbal Shah

Abstract As lowering manufacturing cost and improving resource sustainability is becoming more critical, remanufacturing has attained significant attention in the manufacturing industry. Disassembly is the first step and consumes the most time in remanufacturing. There are three ways to disassemble a part and they are: manual disassembly (MD), human–robot collaborative disassembly (HRCD), and robotic disassembly (RD). RD is a disassembly method using robots without any human intervention and is the focus of this research work. To implement RD, spatial information is crucial. As end-of-life (EOL) products are likely to be discontinued products, the digital models for these products are not likely to be available and determining spatial information using vision systems to facilitate RD may not be possible due to occlusion and inaccessibility caused by restrictive spatial environments such as car under bonnet. However, a digital model of EOL products (including their internal profiles) can be obtained using 3D scan or computed tomography (CT) scan and subsequently, sliced into layers to determine essential spatial information to facilitate RD. Therefore, this research work has proposed to explore the application of slicing technology to assist the RD of a car battery within a car engine compartment where a scanned digital model of the car engine (under the bonnet compartment) is sliced into layers and exported as a text file known as geometry-code (G-code) that contains a large amount of geometrical information that can be used to determine the geometry, location of each component and spatial availability information of an EOL product. The results show that the x, y, z coordinates extracted from G-code can be used to define the spatial availability and identify the barriers and facilitate the creation of collision free paths for RD.

K. W. Ng · H. Y. Chin

Department of Mechanical, Materials and Manufacturing Engineering, Faculty of Science and Engineering, University of Nottingham Malaysia, 43500 Selangor, Malaysia

M. C. Ang (✉) · J. Liu

Institute of Visual Informatics, Universiti Kebangsaan Malaysia, 43600 Selangor, Malaysia
e-mail: amc@ukm.edu.my

A.-L. Kor · M. I. Shah

Leeds Beckett University, Leeds, UK

Keywords Remanufacturing · Robotic disassembly · Sustainability · Slicing

1 Introduction

Remanufacturing plays a crucial role in enhancing the sustainability of natural resources and offers environmental, societal, and economic advantages. It is a significant industrial process applied to end-of-life (EOL) products, aiming to attain performance levels that are either on par with or even surpass newly manufactured products [1]. The initial and critical step in the remanufacturing of EOL products is the disassembly process, which is also the most critical and time-consuming due to the variability in disassembly [2].

The challenges associated with high variability in the disassembly process can be grouped into two groups: physical-related problems and problems linked to the disassembly method. Physical-related problems are problems related to the physical appearance or condition of the EOL product. Some of EOL products are not designed based on the Design for Disassembly (DFD) concept during the product design stage and therefore, causes emergent issues such as product complexity, permanent fastening, and tight part tolerances [3, 4]. In addition to that, corrosion of products also poses a significant hurdle, as it can lead to the binding of adjacent parts, thereby, increasing the complexity of disassembly [4]. Commonly employed methods of disassembly include manual disassembly (MD), human–robot collaboration disassembly (HRCd), and robotic disassembly (RD) [5–7]. Table 1 compares these disassembly methods, highlighting their respective advantages and disadvantages.

Owing to the varying conditions of end-of-life (EOL) products and the intricacies of the disassembly operation, manual disassembly is typically employed. This choice is made due to the inherent adaptability of humans in managing uncertainties

Table 1 Comparisons of different disassembly methods [2, 5, 6, 8–12]

Disassembly method	Manual	Human–robot collaboration (HRCd)	Fully robotic
Mode of disassembly	Only involve human labor	Combination of human and industrial robot	Only involve industrial robot
Advantage	High flexibility Able to handle the uncertainty of EOL products	High efficiency Reduce operating cost Reduce energy consumption Ensure human safety from hazardous material	High efficiency Reduce operating cost
Disadvantage	High cost Low efficiency Time-consuming	Safety issue while human and IR sharing workspace	Low flexibility Digital models are needed to operate

associated with the disassembly process. However, the use of manual disassembly presents significant challenges, which include high labor costs, time consumption, and low efficiency. Additionally, there are also risks to human health when dealing with hazardous and damaged materials, such as a damaged engine which may have corrosive substances [5].

In response to the challenges posed by manual disassembly, HRCD has been implemented in the remanufacturing industries [6]. The industrial robot (IR) proves instrumental in replacing human labor in the disassembly process, efficiently managing high-repetition and high-payload tasks. Nevertheless, the dexterity of IR falls short compared to humans, who possess superior learning abilities. Consequently, a collaborative approach between humans and robots becomes necessary to effectively execute tasks. In the disassembly operation, IR handles hazardous materials and tasks characterized by high repetition and payload, while humans manage delicate or small components requiring extra caution, such as ceramic components and tiny spring [11]. Therefore, the implementation of HRCD has the potential to enhance disassembly efficiency, lower operating costs, and ensure the safety of humans by mitigating exposure to hazardous substances [5]. Nevertheless, the application of HRCD remains challenging due to safety concerns. When humans and robots share a workspace without barriers, there is an inherent risk of hazards. Despite the presence of safety mechanisms designed to prevent collisions between humans and robots, the possibility of accidents still exists [13].

In the context of robotic disassembly, only industrial robots (IR) are utilized throughout the disassembly process. There has been a growing interest in employing robots as a replacement for manual labor in disassembly, driven by the potential of reduced costs, shorter disassembly times, and increased efficiency compared to manual disassembly [2, 9, 10]. Robotic disassembly is typically automated, with industrial robots operating according to pre-programmed sequences during the disassembly process. Consequently, manual disassembly sequence planning (DSP) is necessary before the industrial robot executes its tasks [10].

Several issues related to DSP can impact the efficiency of robot disassembly. Most DSP relies on the presence of the original computer-aided engineering (CAD) model for the end-of-life (EOL) product [14]. However, not all EOL products have their original CAD model, especially those that have been in use for an extended period. Additionally, the EOL products may deviate from the original CAD models after prolonged usage. To address this challenge, a 3D CT scanning system can be employed to scan the product and export the model as an STL file [15].

Apart from DSP, disassembly path planning (DPP) is also essential for robotic disassembly. DPP involves computing collision-free paths for the robot, ensuring that there are no collisions between products and the industrial robot during the disassembly process [16]. Accurate disassembly paths require information on the geometry, location of each component, and spatial availability of EOL products, which can be extracted from the computer-aided design (CAD) model or 3D scanned model of the products.

Considering the identified challenges in disassembly for remanufacturing, the following is a list of relevant research objectives:

1. Investigate the use of slicing technology to extract product profile information to determine spatial availability necessary for disassembly;
2. Distinguish between the 3D profiles of spatial availability for disassembly and spatial barriers (geometry) by analyzing the extracted data from the G-code file;
3. Develop a 3D spatial availability model to facilitate robotic disassembly path planning;
4. Conduct simulations of robotic disassembly processes using a predefined disassembly path obtained from objective 3 in a case study.

The G-code, generated through slicing technology, contains extensive geometric information, including Cartesian coordinates. This information can be utilized to ascertain the geometry, location, and spatial availability details of 3D models. A case study has been proposed, utilizing data from G-code, and several software tools employed in this study include Ultimaker Cura, SolidWorks, and RoboDK.

2 Methodology

Figure 1 illustrates the methodology's flow chart which encompasses a total of 8 steps in this study. The initial 3 steps involve pre-processing which focuses on preparing the CAD model and gathering data from slicing technology. The fourth step includes data extraction, where valuable information is extracted from the G-code file of the model. Following this, the subsequent 2 steps are dedicated to modeling, utilizing the data extracted from the G-code to construct a new CAD model. The final 2 steps involve robot simulation, where the positioning and disassembly path are determined within the robotic software.

2.1 Pre-processing

In this study, the disassembly process in robotic disassembly (RD) relies on the CAD model of the end-of-life (EOL) product. This model can either be the original CAD model or can undergo 3D scanning or CT scanning to obtain the necessary geometric model. In this particular study, a car battery located within the car engine compartment is selected as the case study, and its CAD model is crafted using SolidWorks. Figure 2 depicts the CAD model representing the car engine compartment. Within the car engine compartment, the car battery is positioned in the right corner, with a bonnet at the top, and the blocks symbolize other car components. The model is then transformed into a Standard Tessellation Language (STL) file and introduced into 3D printing software such as Ultimaker Cura, for the slicing process. The outcome of the slicing can be previewed in layer form, and in the case of this model, there are a total of 678 layers. Figure 3 provides an overview of the model, while Fig. 4 showcases

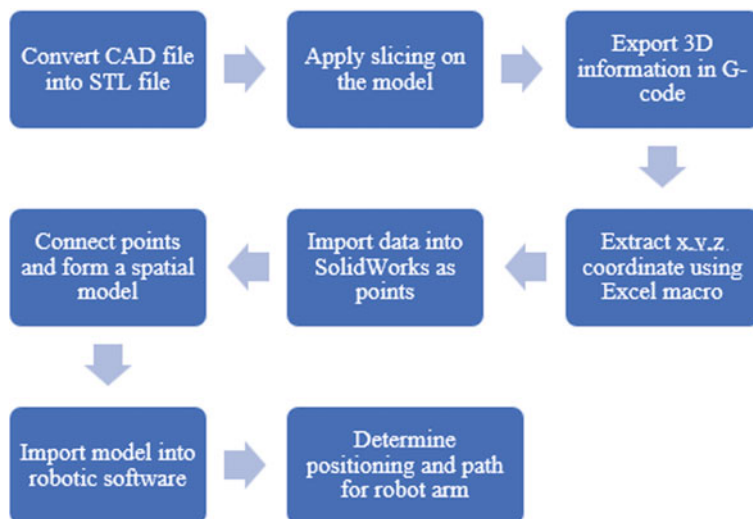
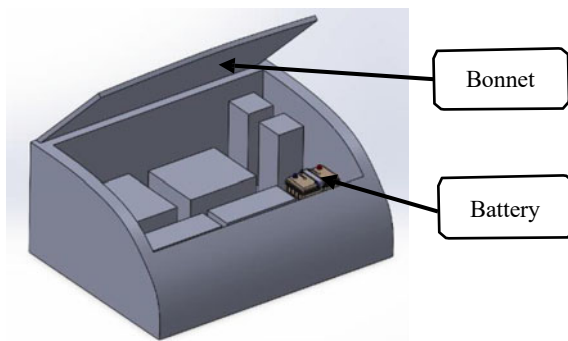


Fig. 1 Flow chart of the methodology

Fig. 2 The CAD model for car engine compartment



layer 188 of the model post the application of slicing. Following the slicing process, the 3D printing information is exported as a G-code file for further data analysis.

2.2 Data Extraction

There are three types of infill styles present in the G-code, namely inner wall, outer wall, and fill, as illustrated in Fig. 5. The outer wall, marked in red, is the exterior layer that forms the edge of the wall, usually consisting of a single solid layer. The inner wall, represented in green, is located beside the outer wall and positioned more towards the center of the model. Typically, the inner wall comprises 2 to 3 layers

Fig. 3 Model after slicing

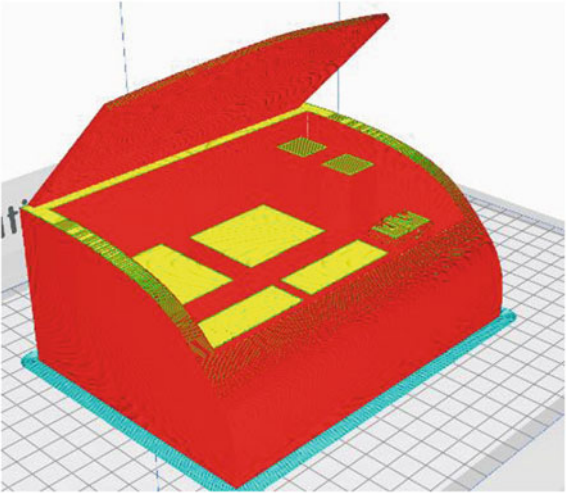
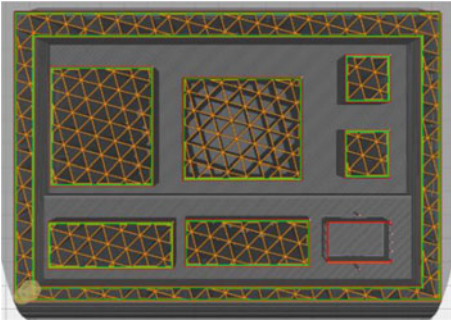


Fig. 4 Top view of layer 188



of solids. The fill, depicted in orange, represents the inner solids filling within the boundary of both the outer and inner walls, occupying the space between them.

Given that the primary objective of this study is to ascertain the geometry, component location, and spatial availability information of the model, the required data pertains only to the outer wall, which outlines the model. Consequently, data related to the inner wall and fill are disregarded. Figure 6 provides an example of G-code containing information for the outer wall infill. In the G-code, the first line commands G1, representing linear interpolation, while X and Y denote coordinates, and E indicates extrusion volume.

The G-code file containing 3D printing information is converted into a text file and exported to Excel for data extraction. Figure 6 shows the G-code in line form. To extract the coordinates, the Excel Power Query tool, specifically ‘split column by delimiter,’ is employed. This process involves splitting the x, y, and z coordinates into separate columns, and any unnecessary data is subsequently removed. Figure 7

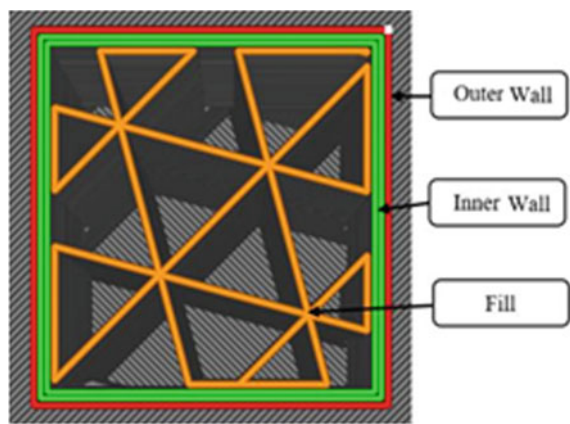


Fig. 5 Type of infill for sliced model

```
; TYPE:WALL-OUTER
G1 F600 X79.184 Y179.993 E132.46142
G1 X79.184 Y60.407 E134.03605
G1 X238.764 Y60.407 E136.13731
G1 X238.764 Y179.993 E137.71194
```

Fig. 6 The G-code for wall outer

✕ ✓ <i>f_x</i> = Table.Skip("#Removed Blank Rows",3)			
1.2 Column1.1.2.2.1 ▼	1.2 Column1.1.2.2.2.1 ▼	1.2 Column1.2 ▼	
1	null	0.2	
2	244.513	null	
3	243.497	null	
4	242.274	null	
5	240.898	null	
6	239.434	null	

Fig. 7 Application of excel power query to extract x, y, z coordinates

demonstrates the application of ‘split column’ in Excel Power Query to extract x, y, and z coordinates.


```

Dim swApp As Object
Sub main()

Set swApp = Application.SldWorks
Set Part = swApp.ActiveDoc
swApp.ActiveDoc.ActiveView.FrameState = 1
Dim skPoint As Object

Open "C:\Users\chinh\Documents\Mechanical Year 4\FYP\g code solidworks\all.txt" For Input As #1
Part.SketchManager.Insert3DSketch True
Do While Not EOF(1)
Input #1, X, Y, Z
Set skPoint = Part.SketchManager.CreatePoint(X, Y, Z)
Loop
Close #1

Part.ShowNamedView2 "*Isometric", 7
Part.ViewZoomtofit2
End Sub

```

Fig. 8 SolidWorks macro codes [17]

Fig. 9 Points of wall-outer
infill



2.3 Modelling

Once all the coordinates of the outer wall infill are extracted, the data is imported into SolidWorks as 3D sketch points using a SolidWorks macro based on the codes from the GRABCAD Community [17] as depicted in Fig. 8. In total, there are 24,688 points. Figure 9 illustrates all the points successfully imported into SolidWorks. These points can be employed to generate the model's outline, with the points connected by lines to form a solid body, as shown in Fig. 10. The blue region denotes the spatial extent of the model.

3 Robot Simulation

In this study, the model is transformed into an STL file and brought into the robotic simulation software, RoboDK, to ascertain a collision-free path for the disassembly process. The arrangement of the robot arm and the car engine area model within RoboDK is depicted in Fig. 11. The Universal Robot (UR16e) is employed as the robot arm in this study and is located to the right of the model.

Fig. 10 The space and solid body formed by points

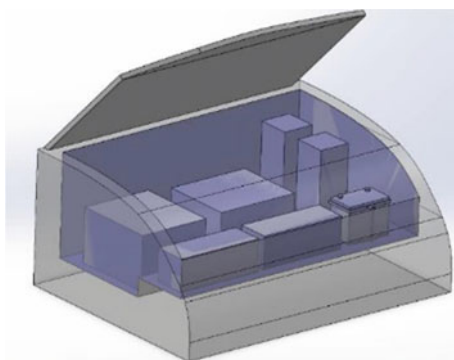
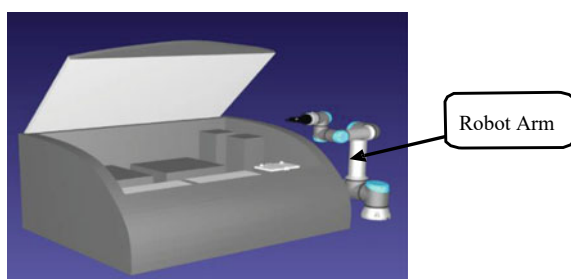


Fig. 11 The arrangement of the robot arm and the car engine



To establish a precise disassembly path, it is essential to possess information regarding the geometry, location of each component, and the free spaces within the model. In this study, the focus is on the nuts of the battery, which serve as the designated disassembly targets. Figure 12 illustrates the locations of these nuts, highlighted in red. The precise nut locations can be extracted from SolidWorks, with the x, y, z coordinates of the nut centers provided in Fig. 13. Subsequently, a collision-free path is manually devised, aligning with the empty spaces within the model, as depicted in Fig. 14. The yellow line signifies the path of the robot end effector for the disassembly of the right nut. To generate this path in RoboDK, several goal points must be set. There is a total of 4 goal points, encompassing the initial position of the robot arm and the right nut. In Fig. 14, goal point 1 denotes the starting position of the robot arm end effector, while goal points 2 and 3 denote intermediate positions for the robot end effector to reach within the predetermined spatial availability obtained from the G-code-extracted information. Finally, goal point 4 represents the final position of the end effector for the disassembly of the right nut. Figure 14 also illustrates the orientation conditions of the robot arm at these 4 goal points.

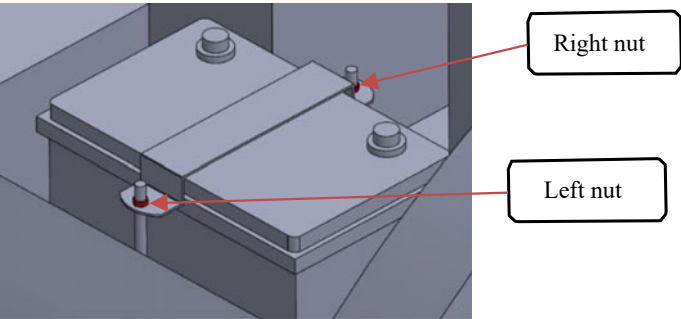


Fig. 12 Left and right nuts for the battery

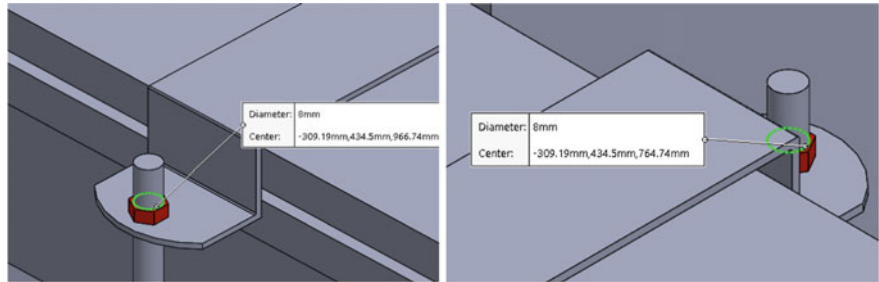


Fig. 13 Precise coordinates of the centres of the left nut and right nut

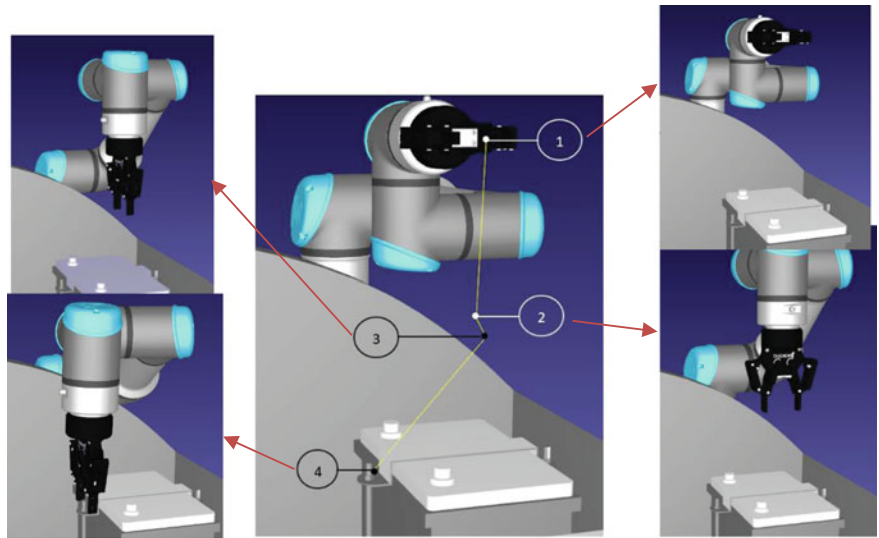


Fig. 14 Disassembly path and orientation conditions of robot arm at four goal points

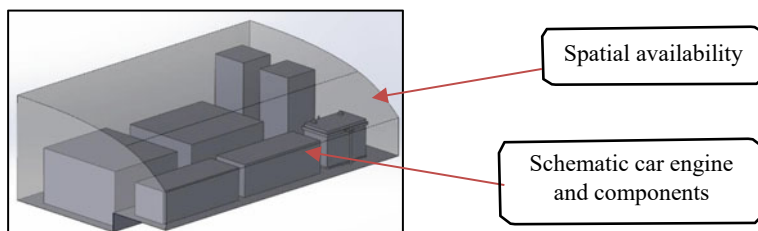


Fig. 15 Spatial availability information of car engine compartment model

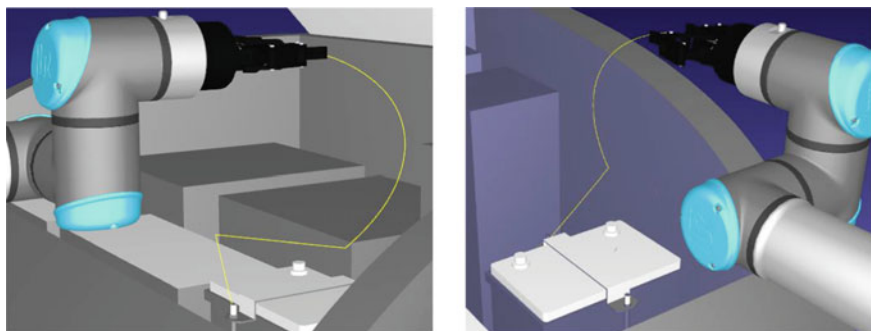
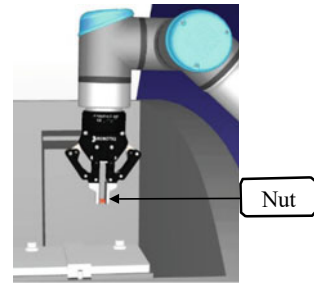


Fig. 16 Two more potential disassembly collision free paths

4 Discussion

The slicing technology enables the determination of the spatial availability within the car engine compartment model as shown in Fig. 15, derived from data obtained through slicing technology. Once the spatial availability is established, one or more collision-free paths can be manually devised for the disassembly of the battery nuts. Figure 16 illustrates two additional potential robot paths for nut disassembly, with the robot positioned at different locations and the yellow line representing the paths. With these results, the disassembly of the nuts from their mounting locations for the battery are successfully demonstrated with the end effector of the robot travelling paths shown. Figure 17 shows the end effector of robot arm that is gripping the disassembled nut.

Fig. 17 Gripper gripping right nut



5 Conclusion

In this research, an investigation into the utilization of slicing technology to aid and streamline robotic disassembly processes have been conducted. From the methodology and observed results, the following findings have been attained: (1) the geometrical information derived from G-code can effectively define the spatial availability and identify geometric barriers for a product undergoing disassembly; (2) leveraging the geometrical details extracted from the G-code allows for the precise determination of the targeted position of the part to be disassembled, exemplified in the case study involving battery disassembly; (3) by considering the spatial availability, geometric barriers, and part positioning information extracted from the G-code, it is feasible to manually and potentially automatically create multiple collision-free paths for a robot arm to execute the disassembly of end-of-life (EOL) parts, exemplified by the disassembly of the locking nuts securing the battery.

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Image-Based Incremental Learning for Part Recognition of Used Automotive Cores in Reverse Logistics



Clemens Briese , Vivek Chavan , Marian Schlueter , Jan Lehr ,
and Ole Kroeger 

Abstract This paper presents a study on image-based incremental learning for part recognition of used automotive parts, also known as cores. The use of Machine Learning (ML) in the recognition of used parts has proven to be effective in suggesting Original Equipment Number (OEN) based on images and logistics data of a core. This leads to a four-eye process where the worker and ML interact through an assistance system. In reverse logistics, the spectrum of parts handled is constantly changing, making it difficult to have a “complete” image or sensor-based data set. The study focuses on the ramp-up phase of an ML implementation project in a real-world automotive core sorting station. There are two stations equipped with sensors such as RGB cameras. The sorted parts were acquired over a period of one year. Incremental learning was employed to cope with the growing dataset and the growing number of classes to be identified without retraining a model from scratch. Open source and state-of-the-art incremental ML learning methods such as POD-Net and Foster were tested against the common joint training approach used for most benchmarks in computer vision. The best-fitting open-source method for this problem was identified as POD-Net used with a self-supervised pretrained ResNet50. For the ramp-up of an ML-based core recognition a combination of incremental learning and joint training was found to be useful. It starts learning from a small number of digitized parts (14 classes), while maintaining a high recognition accuracy rate throughout the year, with a final class count of 100 (an increase of approx. 600%), which is a subset of a real application problem. The results of this study show that the proposed method is efficient, plastic, and energy-saving. Thus, it is a promising approach for the recognition of used automotive parts.

Keywords Incremental learning · Part recognition · Reverse logistics

C. Briese (✉) · V. Chavan · M. Schlueter · J. Lehr · O. Kroeger
Fraunhofer Institute for Production and Design Technology (IPK), Pascalstr. 8-9, 10587 Berlin,
Germany
e-mail: clemens.briese@ipk.fraunhofer.de

1 Introduction

1.1 Project Context

The reuse and remanufacturing of end-of-life parts (cores), e. g. in the automotive aftermarket, has become increasingly important to reduce the CO₂ footprint of components and thus reduce product life cycle costs [1]. Therefore, a defective car part is firstly extracted from a vehicle, then collected from workshops and shipped to warehouses where they are identified and sorted. During sorting, a core is evaluated to certain criteria whether to process for reuse, remanufacturing or material recycling. In industry, the identification and evaluation of cores is performed almost exclusively manually by workers and relies heavily on the readability of labels on the cores which are often dirty, hard or even impossible to read due to damage. To support this, we presented in previous work [2] an AI-enhanced part recognition approach learned on image, logistics, and customer data independent from labelled data.

During the project, these data sets were collected at three workstations of the application partner, a reverse logistics provider for sorting and routing automotive cores. Approximately 450,000 parts were recorded in 2 years, starting from 2020.

The purpose of this paper is to support future decisions on the type and interval of training in applications with high class turnover.

1.2 Related Work

Incremental Learning (IL), also known as continual or lifelong learning is a Machine Learning (ML) paradigm that deals with the accumulation of knowledge from previous tasks and learning incrementally [3], in which training is performed on an incomplete data set that is augmented at specified time intervals. IL approaches aim to resolve the dilemma between model plasticity (ability to learn from new data) and rigidity (ability to retain previously learnt knowledge) [4]. Class Incremental Learning (CIL), with incremental addition of new classes is one of the most challenging ML scenario [5]. State-of-the-art implementations of CIL incorporate a combination of regularization methods, fine-tuning, model expansion and exemplar storage (storing a limited amount of data from old classes) [6].

In continuous data acquisition environments, large data streams are generated that are not suitable for post-process use, as they would require high storage capacities. In particular, the continuous acquisition of multi-view image data for object recognition generates large amounts of data. IL with data pooling or sample storage represents a way to reduce the resources and energy required for storing and processing these images.

In this paper, we show the potential of IL based learning for applications with high variation in the class structure. Next to the presence of a continuous data stream, there

are other reasons for the use of IL, e.g. the instant need to derive outputs and adaptive predictions from the incoming data in application areas of robotics, wayfinding or web traffic monitoring [7–9]. Autonomous robotics and human–machine interaction are inherently incremental, as data arrives as a stream of signals with potentially large drift. In the fields of autonomous control, service robots, computer vision, self-localization, IL paradigms have been developed [9]. The authors implement and test for the incremental algorithms that can be applied to a human inspection and evaluation process in reverse logistics.

The authors of this paper demonstrate the sustainable advantage of incremental over monthly batch-trained data in identifying core streams with business and sensor data in a real-world scenario.

In methods with data pooling, the size of the data set that the algorithm learns grows with each iteration. In learning methods without data pooling, the model is changed using only the input variables measured in each iteration. The authors in this paper use both methods and achieve acceptable accuracy and lower environmental impacts with the methods without data pooling.

A cornerstone for Class IL implementations is incremental classifier and representation learning [10]. It introduced herding, a greedy strategy for selecting exemplars from old classes; the model retrains on the exemplar data along with the newly added data during each increment. PODNet is specifically aimed at long runs of incremental learning tasks [11]. They incorporate a spatial-based distillation loss, along with representation learning for dealing with catastrophic forgetting in older classes, where others identified reasons for catastrophic forgetting and poor incremental learning [12].

Mittal et al. conclude that the quality of feature representation during the initial joint training has a significant impact on incremental learning in subsequent tasks. Yan et al. (2021) [13] implemented Dynamic feature structure for Class Incremental Learning with a lot of success in their approach called DER.

Along similar lines, FOSTER [14] aims to introduce a dynamic model architecture along with feature compression to tackle the problem of increasing model size in approaches like DER.

Most papers (75–90%) in ML research focus on, and report accuracy metrics, whereas only 10–20% report efficiency results [15]. A similar trend is seen for CIL. Computing time and the associated carbon footprint, as one possible additional metric, plays a central role in the field of continual learning, however, none of the published research includes information on it [4, 6] also emphasize the need for realistic testing with variable class increment sizes. We aim to address these issues in this paper.

1.3 Structure of the Paper

In the second section, the materials and methods underlying the paper are presented. The real problem is defined in more detail and data set collected in the project

is presented. Then the methods are presented and evaluated. In section three, the experiment and the results are described and then discussed. Finally, the conclusion is given in section four.

2 Materials and Methods

In this chapter, incremental learning methods are chosen, and our experimental design is described. From the EIBA data set, a virtual ramp-up phase for the first year is retroactively derived, representing data collection and ML training with IL compared to traditional batch learning approaches.

2.1 Problem Statement

A variety of challenges arise in the image-based identification of used parts:

The complexity due to the variety of parts within one class or OEN makes accurate classification difficult. Each end-of-life part has specific characteristics and properties that must be considered to enable precise classification.

High complexity also requires more data. AI systems need a certain amount of data to learn effectively and make accurate predictions. The required amount is connected to the complexity of the present problem.

Sorting companies often do only possess or have only limited access to data of the used parts they are handling. Least have their own stock of used parts, so **comprehensive initial data sets are not present and cannot be created**. Instead, data must be collected during the process, resulting in an unbalanced data distribution. This raises the question of which data should be used for training and what are reasonable training intervals.

In the circular process, already known parts come in irregularly and new parts appear continuously in the sorting program. This dynamic leads to a **constant change in the number of classes** and puts the adaptability of an AI system to the test.

Collecting image data during the process by teaching and using AI to identify used parts can require **significant computing power** and thus energy. This can lead to an ecological burden and increase the cost in time and money.

An AI application that learns continuously and incrementally requires a **trade-off between the accuracy of the results and the associated training overhead**. Highly accurate AI models and methods may require more training data and computational resources, while less sophisticated models need less but may not achieve the desired accuracy.

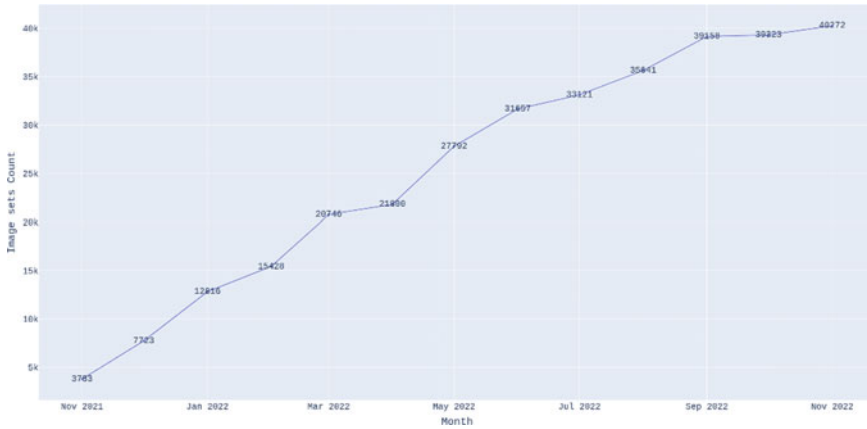


Fig. 1 Number of collected image sets over one year

2.2 Dataset

The period chosen for the study in this paper is November 2021 to November 2022.

One “image set” consists of three RGB and three depth images.

As shown in Fig. 1, within the time span the data set grows to about 40,000 sets, and about 3,000 classes, each representing a type of automotive core and its original equipment number (OEN).

During the data collection phase, the OENs are examined in a chronological analysis to provide an overview of the relationship between the amount of OENs of the incoming cores. Looking at the cores handled by our research partner, several challenges to successful identification become apparent.

The data set contains thousands of classes with a strong imbalance. Some classes occur with high frequency, and about 2,000 occur only once after one year.

For this paper, a subset of those 3,000 classes was used. A class is considered trainable for image recognition if it has more than 20 recorded image sets. With this condition, we have a pool of 325 newly learned classes in the period from Nov. 21 to Nov. 22 (Fig. 2). Starting with 25 classes and final 350 classes results in an increase of 1300% with a growth of about 27 new classes per month on average. Such initial increases are exemplary for ramp-up phases and slow down over time. This can also be seen in Fig. 3, in the last months the number of classes is not increasing so much.

2.3 Methods

IL versus batch learning for image-based part recognition

Training AI models for image-based classification is commonly achieved by a batch learning and joint training approach, which uses all available data and trains



Fig. 2 Cumulative collected overall OENs (blue) and the amount of OENs with more than 20 image sets

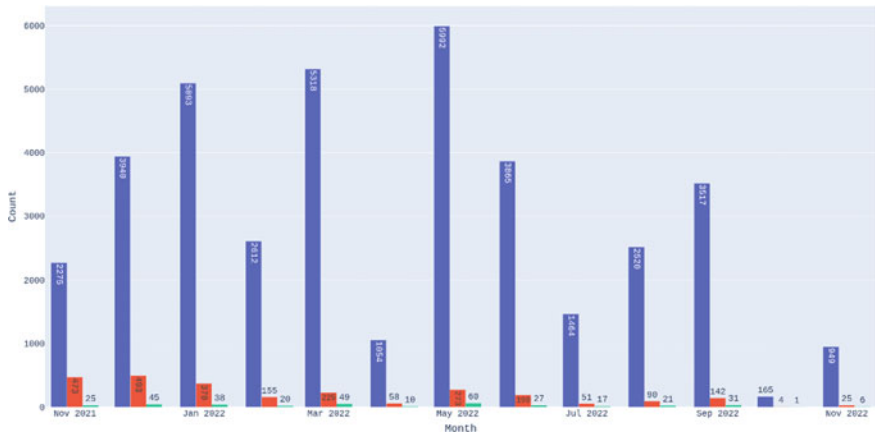


Fig. 3 Distribution of new classes (blue), OENs (red) and new OENs with more than 20 image sets (green) collected per month

a model from scratch to solve a given task. Following the idea of transfer learning, usually, a pre-trained model (e.g. a model trained on ImageNet) is used to initialize an ML model. Thereby, the model does not have to learn common feature extractions from scratch, which leads to a better generalization of the model and speeds up the learning. However, a joint training approach is not energy and time efficient for iterative problems (where new classes and data are appended to the data set) for two reasons: data sets explode without data set pruning techniques and learned knowledge from a previous training iteration is discarded. In contrast, in IL previous knowledge is retained.

Based on the requirements and preliminary knowledge of this project [2], the aforementioned class incremental learning approaches were tested on different data sets and the performance metrics, viz., Top-1 accuracy on older and newer classes, training time and energy consumption changes between the increments, and AUC (Area Under the Curve) were monitored. ResNet50-backbone is used in accordance with other CIL studies. In past research we tested four state-of-the-art methods: PODNet, DER, FOSTER, POD-AANet. For testing we used publicly available datasets and internal data for the analysis, after which, we chose PODNet for further Studies. PODNet [11] showed a good overall performance, even over longer sequences of incremental steps of varying sizes, with a negligible ramp-up in energy consumption between the increments. Furthermore, the supplementary image data belonging to older classes can be periodically introduced to the model for online learning, which can help in improving the accuracy of prediction.

This section illustrates an iterative training problem for image recognition tasks with in-process data and compares the accumulated needed GPU time of a joint training approach vs. a set of alternative approaches based on data set pruning and incremental learning. Pruning means in this context, that in every month only the most important data points are selected for future training.

3 Results and Discussion

In this section, the results of the Incremental Learning approach are contrasted with the Joint Training approach and evaluated.

3.1 Results

In order to keep the experiment time low, we concentrated on one subset of the 100 classes of the data set, the condition that at least 20 usable image sets exist is maintained. The distribution of the classes is shown in Fig. 3. The subset represents the original dataset accurately enough.

The increase of new classes occurs primarily in the first 5 months. The study starts with 14 classes in November 2021 and ends with 100 classes in November 2022, an increase of approx 600% (Fig. 4). In the subset, a large increase in the number of classes also occurs in the first few months and then levels off, similar to the complete dataset above.

The experiments were conducted on a standalone PC with one NVIDIA A6000, and an AMD Ryzen Threadripper 3960X with 24 cores and 128 GB of RAM.

Table 1 shows the results for incremental learning after each month versus full learning of all available classes after one year. Incremental learning shows a performance gap after one year of 10% top-1 and 3.3% top-5. It is interesting to note that there are months when the performance of IL increases (see February, March,

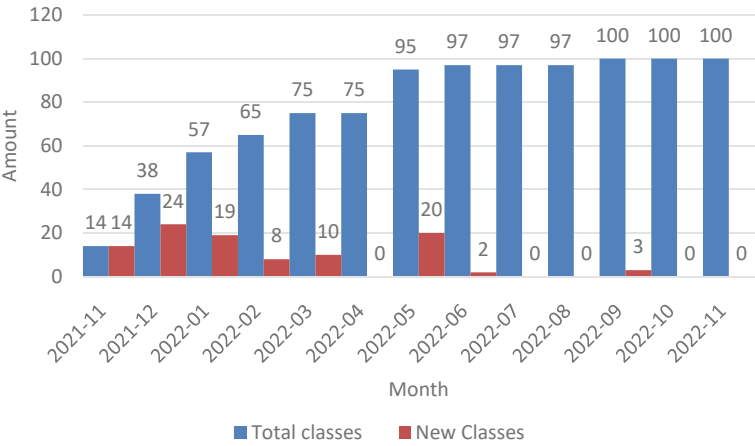


Fig. 4 Distribution of newly acquired classes with more than 20 image sets for the investigated subset of up to 100 classes

August). This is due to the pre-processing of the data. By collecting new data, more suitable data could be chosen for training.

The loss in recognition performance is offset by the savings in training time. Thus, over the year, the IL approach comes to 11.2 GPU hours of training time, while the monthly joint training comes to 54.3 h (see Tab. 2). This is approximately five times

Table 1 Performance results of the study IL vs JT for the given subset over of one year

Month	Total classes	New classes	New images	CUM. images	IL TOP-1 ACC (%)	IL TOP-5 ACC (%)	JT ACC: TOP-1 (%)	JT ACC: TOP-5 (%)
2021-11	14	14	2195,00	2195,00	93.95	100	93.95	100
2021-12	38	24	4406,00	6601,00	89.4	97.76	–	–
2022-01	57	19	6135,00	12,736,00	88.54	96.93	–	–
2022-02	65	8	3313,00	16,049,00	92.85	98.51	–	–
2022-03	75	10	6772,00	22,821,00	87.1	96.54	–	–
2022-04	75	0	225,00	23,046,00	88.48	96.83	–	–
2022-05	95	20	7703,00	30,749,00	86.5	96.13	–	–
2022-06	97	2	3705,00	34,454,00	80.48	94.66	–	–
2022-07	97	0	806,00	35,260,00	77.97	93.02	–	–
2022-08	97	0	1815,00	37,075,00	81.47	94.7	–	–
2022-09	100	3	2453,00	39,528,00	82.2	95.8	–	–
2022-10	100	0	0,00	39,528,00	82.2	95.8	–	–
2022-11	100	0	757,00	40,285,00	82.2	95.8	92.04	99.13

Table 2 Comparison of GPU time spent between IL and JT and the approximate cost of cloud training

Method	GPU-time [h]	Approx cost [€]
IL training	11.2	78.4
Approx. monthly joint training	54.28	380

the effort. Considering the costs, assuming that a comparable VM in Microsoft Azure costs about 7€ per hour, this results in a saving of 310 € over the year, or 79%.

3.2 Discussion

In this work we compared incremental learning against joint training approach for the image-based core recognition in the automotive aftermarket in terms of accuracy, energy and time consumption. Our experiments showed that the incremental learning approach is able to save a high amount of time and cost but comes with a significant loss of accuracy.

Compared to a significant Top-1 loss of ca. 10%, the loss in terms of Top-5 accuracy is lower at ca. 3% and acceptable considering the application as an assistance system. The difference in the performance metric between Top-1 and Top-5 suggests that the IL approaches are basically good at learning new classes, but have problems in distinguishing very similar objects.

Of course, the setup considered in this project saves only 310 € and is negligible at business level, but this counts only for 100 objects. The savings scale with increasing number of classes.

In contrast, even with the small number of 100 classes the time saving potential of ~43 GPU-hours is notable. The training time of incremental learning with data pruning does not exaggerate compared to joint training time, which correlates exponentially with the number of classes/data samples.

Basically, the results show that IL brings a significant efficiency and cost advantage when working with AI systems in the form of assistance systems, which rely on high Top-3/Top-5 values and do not necessarily require high Top-1 values.

By dynamically controlling the intervals for joint training, the trade-off between performance and effort can also be reduced. Often, processes that require a large change in class composition are known in advance. For example, due to a ramp-up, a restructuring of the warehouse or influences from supply chains. A change from joint training to incremental learning can efficiently cover this phase of high turnover and when these phases are over joint training can reduce the performance gap again. These event-driven changes between JT and IL can thus combine the advantages of both forms of training.

4 Conclusion

Our research has shown that an intelligent combination of Incremental Learning and Joint Training has significantly increased training efficiency, saving 76% in training costs. The associated trade-off in terms of Top-5 performance is 3% and Top-1 is 10% over the period of one year and an increase in the number of classes by 600% in this time. These are acceptable losses in most cases when dealing with application in the form of assistance systems, which are widely used especially for the support of logistic processes. The saving of approx. 79% GPU time and the associated costs and energy shows the potential of incremental learning in ecological and also economic terms.

The paper shows that incremental learning in phases of high class turnover followed by joint training in the consolidation phase is an efficient learning strategy.

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Ensemble Learning for Estimating Remaining Useful Life: Incorporating Linear, KNN, and Gaussian Process Regression



Nima Rezazadeh , Donato Perfetto , Alessandro De Luca ,
and Francesco Caputo

Abstract Assessing the remaining useful life (RUL) of components is essential for decision-makers in various industries, including manufacturing, transportation, and aerospace. By providing a reliable estimation of how long a part can continue to operate effectively, RUL assessment can inform decisions regarding maintenance, repair, or replacement of the component. To develop a technique for estimating the RUL of a system that is both highly accurate and less time-consuming than current methods, firstly, using the principal component analysis (PCA) manner, features were extracted in a reduced format; then, a hybrid model, i.e., an ensemble model that combines linear, k-nearest neighbors (KNN), and Gaussian process regression (GPR) through weighted averages, was designed. The well-known C-MAPSS dataset from NASA was employed to evaluate the performance of the model. To optimize the model's performance, an optimization procedure, i.e., constrained nonlinear multi-variable was applied to identify the tuned weight in the ensemble learning that minimized the root-mean-square error (RMSE) value. Findings indicated that the optimized hybrid model outperformed the linear, KNN, and GPR models separately, as well as many of the prior investigations dealing with the same dataset, as evidenced by its lower RMSE value and the execution time.

Keywords RUL · Linear · KNN · Gaussian process · Ensemble model · Optimization

N. Rezazadeh (✉) · D. Perfetto · A. De Luca · F. Caputo
Department of Engineering, University of Campania “Luigi Vanvitelli”, 81031 Aversa, Italy
e-mail: Nima.rezazadeh@unicampania.it

1 Introduction

Although throughout the design stage, a limited number of cycles (time of performance) is calculated by engineers, several factors can be considered as culprits for a decline from the ideal statistics such as assembly mistakes, material and structural defects, and so on [16].

The duration between the present time and the end of a system's useful life is referred to the remaining useful life (RUL). The term "useful" considers the economic value of the system, which may differ from its technical life span. The RUL of a system is not fixed and can vary depending on its current age, operating environment, and the information obtained from condition monitoring or health assessments. Therefore, RUL can be considered a random variable [3].

When the reliability, budget-friendly, and productivity aspects of predictive maintenance and remanufacturing processes are under consideration, a precise calculation of RUL plays a significant role [8]. Data-driven and physics-based models are the two main categories for estimating RUL, although in recent years hybrid models, i.e., the physic-guided machine learning (ML) models, have been introduced in the field. Data-driven models in RUL estimation can be divided into three groups depending on the data source, notably degenerate (degradation), survival, and similarity models. The former only needs to deal with safety thresholds, whilst the second and third techniques use failure data and the entire history of a similar system (including healthy and failure) data, therefore [7].

Recent advances in ML algorithms have shed light on meticulous and generalized RUL estimation. To this end, three stages should be carried out sequentially. Whether using signal processing or ML processing approaches, a pre-processing step should be performed first. Wavelet transformation and Fourier transform are illustrations of the former; principle component analysis (PCA) is an instance of the latter [3, 17]; thereafter, a learning model ought to be trained using the extracted features. There are numerous ML models in the scope, including linear and polynomial regression techniques, in addition to deep learning networks such as long short-term memory, convolutional neural networks, and things like these areas [11]. Last but not least, the estimation manner's effectiveness should be assessed by counting an appropriate metric including root-mean-square error (RMSE), concordant-discordant, adjusted R-Squared, and so forth.

There are numerous investigations where researchers dealt with ML models for anticipating RUL [21]. To appraise the RUL of the PHM 2012 dataset, Zhao et al. [26] compounded a two-stage supervised dimensionality reduction (using PCA) process with the time–frequency representation acquired utilizing S-transform and Gaussian pyramid. Following that, textural features were calculated; in the final step, multiple linear regression models were compared in terms of their accuracy in the RUL calculation.

Ahmad et al. [1] presented a technique for reliably predicting the RUL of rolling element bearings (PRONOSTIA dataset) by employing dynamic regression models. They applied a quadratic regression model to predict the future values of the health

indicator (HI), which captured the evolving trend over a small window of recent observations. The authors also proposed an alarm bound technique to determine the onset of bearing degradation, using a linear regression model and an alarm bound to determine the time to start prediction. Ultimately, to identify the failure threshold for bearings, the gradient of the bearing HI (that was determined using linear regression) was proposed.

A linear Kalman filter was employed by Baptista et al. [2] to improve the RUL estimation using data-driven models. Linear regression, neural networks, random forests, support vector machines, and k-nearest neighbors were considered for development. A dataset from the engine bleed valve of a commercial aircraft was employed for the assessment of the suggested advancement; it was emphasized that the Kalman-based approaches represent higher accuracy in RUL anticipation.

In their study, Zhou et al. [27] used k-nearest neighbor regression to calculate the RUL for all lithium-ion cells in a battery. Optimization of the effective parameters in the model was carried out using a differential evolution approach. In the technique, a weighted average of the useful life of various cells that had analogous degradation trends was performed for RUL estimation. The more the number of tested cells and nearest cells, the more estimation accuracy according to results. Hu et al. [6] developed a non-linear kernel regression model to assess the reliability of rechargeable Li-ion batteries, particularly those used in medical devices. They used the k-nearest neighbor regression method to construct the model and analyzed the battery charge voltage and current curves. The authors employed particle swarm optimization to reduce the cross-validation error when estimating battery cell capacities. The proposed model accurately predicted the lifespan of Li-ion battery cells based on ten years of cycling data. Madeira et al. [13] compared eleven ML approaches for estimating RUL in the C-MAPSS dataset, which include Lasso regression, polynomial regression, k-nearest neighbor regression, support vector machine, etc.

An effective probabilistic ML model for regression tasks is entitled Gaussian process regression (GPR). GPR formulates the intrinsic distribution of the data using Gaussian processes rather than presuming a concrete functional form for the relationship between independent and response variables [22]. Hong and Zhou [18] applied GPR for bearing feature tracking and RUL prognosis. Experimental results showed high accuracy, and comparisons of different covariance functions were discussed; GPR offered a new approach for predicting fluctuated signals of bearing features. Xu et al. [24] introduced deep learning and nonstationary GPR, a model for authentic RUL estimation with uncertainty quantification. They addressed challenges in high-dimensional features, noise robustness, and time-dependency capture. Benchmarking against other models using the NASA turbofan engine dataset represented superior accuracy and tighter uncertainty bounds.

Reviewing the literature on RUL projection, as far as the authors of this paper are aware, this is the first time that an optimum combination of linear, KNN, and Gaussian regression techniques has been performed for RUL prediction despite the fact that this hybrid technique can be considered a beneficial approach on the condition that the similarity model of the system is present as well as the recorded parameters from the sensors can be utilized directly as feeding features.

The remaining sections of the article are allocated to a description of the used dataset, selection of the most informative sensors, discussion of the employed technique in RUL calculation and finding the optimum average weights, and ultimately analyzing the acquired results plus the conclusion part.

2 Materials and Methods

The performance of an optimized ensemble model for RUL estimation was assessed using the C-MAPSS dataset, which includes similarity data. To this end, the selection of the most informative sensors was initially carried out through a variability analysis. Then, for the feature extraction step, principal component analysis was conducted. Following that, three different regression models, namely linear, k-nearest neighbors, and Gaussian process regression were individually trained on the training dataset. In the testing phase, predictions for the RUL were generated by each of the aforementioned trained regression models. These individual predictions were combined into a final prediction through the calculation of a weighted average. It should be noted that each model's prediction contributed to the final prediction, with the contribution of each model being determined by its weight.

The weights for each model were typically determined during the model training process. Models that demonstrated greater accuracy on the validation data were assigned higher weights, while those that were less accurate received lower weights. The final prediction for the RUL was determined as the result of this weighted average. In essence, the model leveraged the strengths of multiple regression techniques and assigned different levels of importance to their predictions based on their historical performance. The entire work process is presented in Fig. 1. It should be noted that W_1 , W_2 , and W_3 are the allocated weights to the linear, KNN, and Gaussian Process regressors, subsequently.

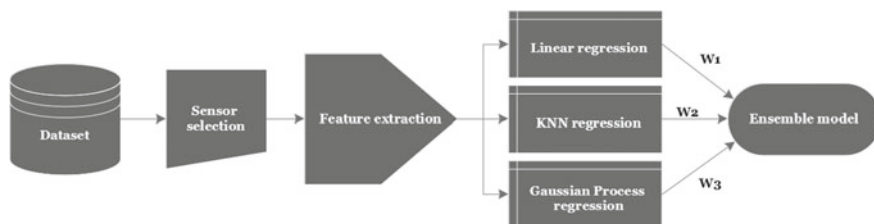


Fig. 1 Workflow of the designed RUL estimator model

2.1 *C-MAPSS Dataset Configuration*

This paper evaluates a hybrid method on the widely used NASA turbofan engine degradation problem, which involves using simulated data from the C-MAPSS dataset [5, 12, 20], consisting of four sub-datasets, i.e., FD001, FD002, FD003, and FD004 with 21 sensors. Each sub-dataset has a training and test set, with run-to-failure sensor records of multiple aero engines (similarity model). This dataset contains information about the speed, temperature, air ratio, and pressure that various sensors in different turbofan parts such as fans, compressors, turbines, nozzle, and combustors recorded [5]. A varying degree of initial wear is included in the training dataset, and the goal is to calculate the remaining useful life of engines prior to system failure. In this article, the FD001 sub-dataset was employed, which comprises 100 engine units for training, 100 engine units for testing, one operating condition, 20,631 training samples, 100 testing samples, 206 average life span (number of cycles), and one fault mode. For the remainder of this article, any reference to the dataset will specifically refer to the sub-dataset FD001 [5].

2.2 *Selection of the Most Insightful Sensors*

The statistics captured by particular sensors demonstrated a lower degree of variation, depending on the dataset analysis. It is essential to eliminate the columns related to these sensors from the dataset in order to preserve the precision of the final results. To address this, initially, the standard deviation of each column (data from each sensor) was calculated, subsequently, a threshold value equal to 0.1 was set and finally, columns with a standard deviation less than the threshold were eliminated. Among the 21 primary sensors, only the data of 11 selected sensors was saved for the next steps. It is worth noting that, to avoid any possible bias, the features in each column were normalized in the range [0 1].

For instance, sensors number 8 and 10 had standard deviations of 0.071 and $2.48\text{e}-14$, respectively, and were removed. Figure 2 illustrates the changes in the one removed feature (sensor number 10), as well as the one remaining feature in the dataset (sensor number 9).

2.3 *Feature Extraction*

Feature engineering is carried out mainly for two purposes. Initially, the informative information is latent and cannot be reached by analyzing the raw signals. Of more importance is the fact that in many conditions the dimension of the raw signal is high, and even though the relationship between the independent and dependent variables will be accessible from the raw data, it can be computationally heavy [25].

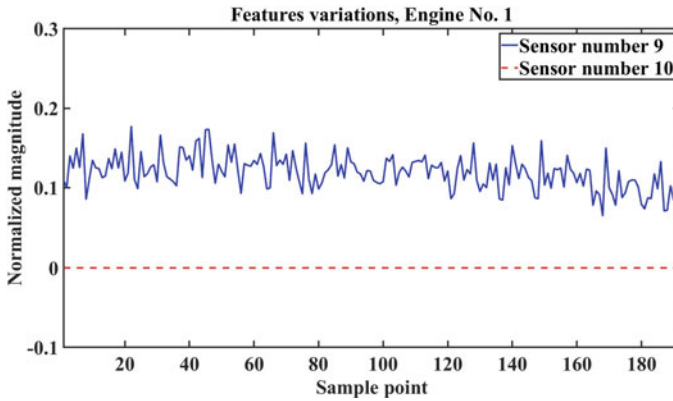


Fig. 2 Changes of recorded data via sensor number 9 and 10 in the training set

There are numerous approaches for extracting health indicators based on the used domain and the employed mechanism. It is worth noting that a feature extraction technique does not always offer a decline in the dimension, for instance, wavelet time scattering increases the dimensions and is useful when the number of samples is limited. For the sake of dimensionality reduction, there are several well-known approaches such as principal component analysis (PCA), independent component analysis (ICA), neighborhood component analysis (NCA), and so forth [25]. Employing a dimensionality reduction step can decline a model's complexity as well as reduce the risk of overfitting.

To reduce the dimensions of a signal X from D data points to d , a series of five primary steps should be followed. Firstly, the standardized form of the signal, X_{stdz} , is calculated by implementing the mean μ and standard deviation σ of the signal. Next, the covariance matrix, denoted as C is computed. Following that, the eigenvectors v and the eigenvalues λ ought to be computed. Then, the principal components should be selected, in this step, the eigenvectors are arranged in descending order based on their corresponding eigenvalues. Subsequently, the top d eigenvectors with the highest eigenvalues are chosen, i.e., matrix W . The standardized data should then be multiplied by the chosen eigenvectors to transform it into the reduced dimension. The following set of equations can be used to illustrate the stages.

$$\begin{aligned}
 X_{stdz} &= \frac{X - \mu}{\sigma} \\
 C &= \frac{1}{D - 1} (X_{stdz})^T \cdot X_{stdz} \\
 C \cdot v &= \lambda \cdot v \\
 Y &= X_{stdz} \cdot W
 \end{aligned} \tag{1}$$

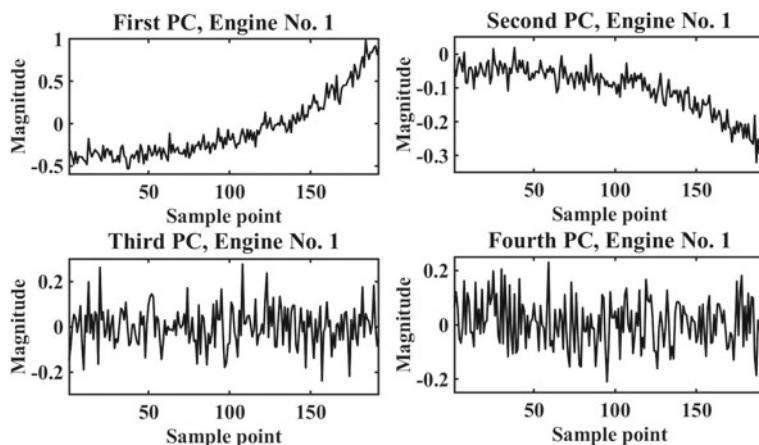


Fig. 3 Changes of the four first PCs in the training set

In order to reduce the number of features to 4, this article employed the calculation of the principal components (PC). The first four ones (scores) were then stored as the features for each scenario.

In Fig. 3, changes for the first four PC on the assumption of Engine No. 1 are depicted. Although the third and fourth principal components (PCs) do not exhibit any observable trends, the first and second principal components indicate variations in an upward and downward direction, respectively, as the sample point (number of cycles) increases.

2.4 Ensemble Model

Compared to traditional model-based procedures, smart data-driven techniques in feature extraction and making differences between different scenarios both in classification and regression tasks have proven their applicability in confronting complicated systems as well as huge data sets in a wide spectrum of fields such as engineering, healthcare, and so forth [15]. The current study employed ensemble learning to combine the RUL estimations of linear, KNN, and Gaussian process regression models using average weights [19]. The main reason for combining a relatively simple regression model, i.e., linear regression with more complex models, e.g., KNN and Gaussian process regression is that the former is more suitable for capturing the entire attitude of the data, the next two, on the contrary, has more capacity in extracting local and nonlinear alteration. As a result, a mixture approach is able to capture a broader spectrum of governing patterns in the data and consequently can result in higher accuracy. Furthermore, linear, KNN, and Gaussian process regression

interpretations are relatively more understandable than methods such as long short-term memory, convolutional neural networks, and generative adversarial network regression.

Linear regression aims to find a relationship between the dependent variable (response) and the independent variables (predictors) in a linear manner. A linear regression model can be formulated as:

$$y = D_0 + D_i x_i (i = 1, 2, \dots, n) \quad (2)$$

where y is the response, x_i is the predictor(s), and D_i is the slope(s) that determines the effects of each independent variable in predicting the response.

While the independent and dependent variables in conventional regression models have a mathematical relationship, KNN regression model is a non-parametric technique, i.e., it attempts to find the response based on the values of the K nearest neighbors to the input data point. There are benefits and drawbacks to this property. One advantage is that the KNN models are more adaptable in their search for nonlinearities than the other models; the disadvantage of this method, on the contrary, can be highlighted as the risk of overfitting [4, 10].

GPRs can be described as probabilistic models that rely on kernels and non-parametric approaches. By estimating the coefficients of a system as a distribution rather than a singular value, this technique aims to effectively minimize uncertainty within the system. The predicted response (y_{New}) for a new set of inputs (x_{New}) can be stated as Eq. 3.

$$y_{New} = \mu(x_{New}) + k(x_{New}, X) [k(X, X) + \sigma^2]^{-1} (y - \mu(X)) \quad (3)$$

in which $\mu(x_{New})$ is the mean of the predictive distribution at x_{New} , $k(x_{New}, X)$ is the vector of covariances between x_{New} and the observed data X , $k(X, X)$ and σ^2 are the covariance matrix and the noise variance in the observed data, respectively, and “ I ” is the identity matrix.

2.5 Optimization Procedure

The designed ensemble model distinguishes between the effects of the linear, KNN, and GPR techniques by allocating the correct weights. As will be shown, finding the optimal weights could improve the accuracy of the estimated RUL using this technique. An optimization process was conducted to determine the optimal weights of the three regression models, which utilized the “fmincon” function in MATLAB®- a non-linear constrained optimization method. This approach implemented an interior-point algorithm to iteratively minimize the objective function by adjusting the decision variable values until a solution satisfying the specified constraints was achieved [23]. The objective function was formulated to calculate the root mean squared error

(RMSE) of the ensemble model and determine its minimum value. The initial weights for the linear, KNN, and GPR were assigned as follows: 0.4, 0.3, and 0.3, respectively. Consequently, the lower and upper bounds for the weights were defined as 0 and 1, respectively. These bounds effectively constrained the weights to fall within the range of 0 to 1, ensuring that the sum of the weights equaled 1.

RMSE is a well-known measure used in regression analysis to evaluate the disparity between predicted and observed values. This metric calculates the average of the squared difference between the expected and actual values. When the RMSE is lower, it indicates that the model is more precise; RMSE can be formulated as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^m (s_t - \hat{s}_t)^2}{m}}$$

(4)

where m , s_t , and $\hat{s}_t$ are the number of prediction points, real value, and the estimated value, ordinary.

3 Results and Discussion

The code trained the linear, KNN, and GPR models on the training data and made predictions on the test data using the three models. The predictions were then combined using the optimized weights to produce the final prediction of RUL.

In the test dataset, real RUL magnitudes for each sample test are available, so by comparing the predicted RUL in term of cycle with the true ones, the accuracy of the trained and tested procedure was investigated using the RMSE metric, and the RMSE values for each engine (100 in total) were stored in a vector.

In previous studies that used the same dataset, the average RMSE values of the 100 engines were commonly used as a metric to evaluate the techniques utilized. Table 1 displays the results of four highly rated methods that were evaluated on the same dataset, in addition to the method suggested in the present study.

The provided table indicates that although the suggested method is fairly simple to execute and does not demand high-end hardware for calculations, it still provides reasonable accuracy. The histogram depicted in Fig. 4 represents the distribution of

Table 1 Comparison of different approaches using the same data set

Technique	RMSE
TaFCN [9]	13.99
DCNN [12]	12.61
MCA-BGRU [9]	12.44
Proposed method	12.44
LSTM (O. [14])	7.78

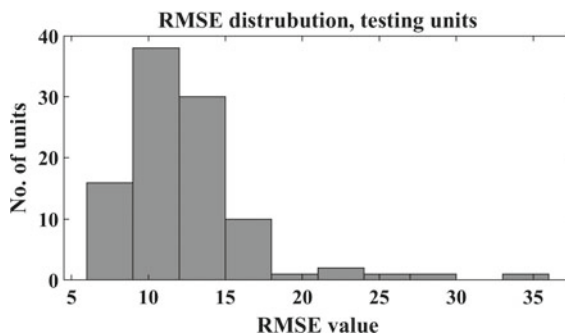


Fig. 4 Distribution of RMSE value of RUL estimation in testing units

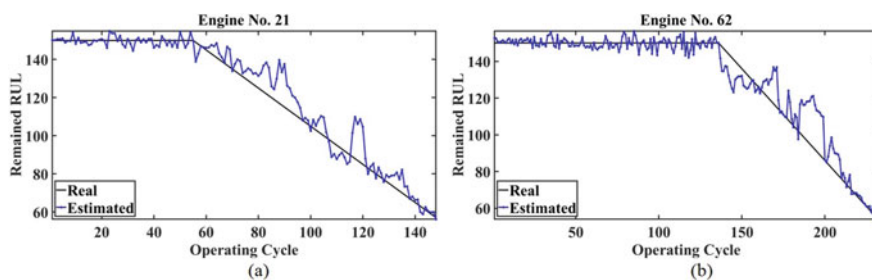


Fig. 5 Estimated RUL versus RUL in testing set, **a** engine no. 21, **b** engine no. 62

RMSE values across all 100 engines. It is understandable that approximately 84% of the test samples had RMSE values that fell within the range of 6 to 15.

After comparing the labeled remaining cycles in the testing dataset with the estimated RUL, it was found that the designed network was better at predicting RUL closer to the actual value for stable regions rather than zones with severe slopes (near failure). As an illustration, for two engines, i.e., number 21 and number 62 run-to-failure RUL estimates are plotted in Fig. 5-a and b, therefore.

4 Conclusion

A reliable RUL estimation and at the same time a less time-consuming procedure plays a significant role in informing authorities regarding the appropriate time of predictive maintenance action as well as remanufacturing measures. Since for a vast majority of industrial systems, the governing physical laws are not accessible, advancing data-driven RUL prediction techniques seems to be an avoidable necessity in the current era.

To this end, ML-based regression models have been employed widely. These methods can be used two-fold, i.e., discovering informative condition indicators automatically from the raw data, and predicting future conditions of systems based on the relationships between the independent predictors (mainly extracted features) and the dependent response. This study employed a combination of linear, KNN, and GPR models to estimate RUL, which were blended using appropriate weights in an ensemble model. The FD001 subset of the C-MAPSS dataset provided by NASA was used to evaluate the performance of the proposed method. In the first step, data from sensors that did not show enough variabilities were eliminated from the training and testing data sets. The first four principal components were then extracted and stored to reduce the dimensionality and extract features. Next, the optimal weights were determined using a non-linear constrained optimization procedure. Finally, the optimized combined model was trained and tested using the related data sets. Average RMSE values for the testing units showed that the proposed manner can predict RUL effectively.

In future works, the proposed method can be applied to real data sets, and the feature extraction step can be further developed to improve accuracy.

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Surface Defect Recognition and Invalidation Judgment of Remanufactured Gears Based on Machine Vision



Fulin Wang, Nengyi Tang, and Xiyuan Leng

Abstract To improve the disassembly automation of remanufactured products and solve the blindness problem in the manual disassembly process, this paper proposes a method about remanufactured product defect gear invalidation judgement based on the improved YOLOv5 target detection algorithm combined with image processing technology. Aiming at the background interference problem in the recognition process, Squeeze-and-Excitation Networks (SENet) is added to the detection model of You Only Look Once version 5 (YOLOv5) to improve the target detection capability of the model. Then exporting the target detection frame, the redundant background of the target image is eliminated by mask processing, which concentrates subsequent identifications' attention on gear targets. By means of using convex hull detection to judge gear broken teeth defects, and calculating the actual length of cracks by object image coordinate transformation, the method that combines the improved YOLOv5 algorithm model and gear defect recognition realizes gear invalidation judgement. This paper focuses on two parts: identifying gears and gear defects using the YOLOv5 and image processing algorithms. The experiment shows that this method has a good recognition effect on gear broken teeth, and the crack length recognition error does not exceed 1.38%. The whole research improves the rationality and accuracy of gears in the process of remanufacturing and disassembly and provides an effective way for deep disassembly of remanufactured products.

Keywords Machine vision · Surface defect recognition · Gear invalidation judgement

F. Wang (✉) · N. Tang · X. Leng
School of Mechanical and Vehicle Engineering, Hunan University, Hunan 08544, China
e-mail: wangfulin_01@163.com

F. Wang
Hunan Province Mechanical Equipment Green Remanufacturing Engineering Technology
Research Center, Hunan University, Hunan 08544, China

1 Introduction

With the rapid development of science and technology, the speed of product change is accelerating, and there are more and more waste mechanical products. Remanufacturing provides a new way to effectively dispose of waste products and maximize their residual value. Transmission parts, represented by gears, are key components of mechanical products, have high value, and are often selected as remanufacturing objects. Disassembly is the prerequisite for the remanufacturing of waste products. At present, for the disassembly and decomposition of waste products, most of the disassembly methods are simple, inefficient, and not standardized. In the actual disassembly process, the defects of the parts themselves have a great influence on the disassembly method and the selection of disassembly tools. Machine vision technology is introduced into disassembly to identify the disassembly conditions of parts, and increase the pertinence of disassembly through reasonable selection of disassembly methods, which can minimize the damage of parts in the disassembly process and provide a good foundation for subsequent parts remanufacturing.

Currently, the detection and identification of mechanical parts mainly focus on traditional machine learning and deep learning. In terms of machine learning, image processing algorithms such as contour detection, threshold segmentation, and wavelet transform are mostly used to realize defect feature extraction and classification. Erraoudi et al. [1] realized the classification and identification of defective gears by using discrete wavelet variation and principal component analysis; Shi et al. [2] extracted gear defects based on local extremum watershed algorithm and smart edge extraction algorithm. Mark the defect position and calculate the defect area; Tao et al. [3] realized the precise identification of gear teeth through image preprocessing and contour detection, overcoming the difficulty of gear size limit detection; In terms of deep learning, domestic and foreign scholars have carried out defect identification and detection based on various neural network algorithms. For example, Sagar et al. [4] used convolutional neural network CNN and YOLO algorithm to identify defective gears and solved the problem of low quality of gear surface defect detection. At the same time, some scholars combined deep learning with machine learning to achieve more accurate prediction and identification of gear defects [5]. Some scholars combined intelligent optimization algorithms [6] to further improve the generalization ability and recognition accuracy of gear defect detection. The above-mentioned studies mostly focus on the defect identification and classification of individual gears, without further evaluation of the damage degree.

As a single-stage target detection algorithm, YOLOv5 has a light network structure and fast recognition speed, and is widely used in industrial applications. However, for gear target recognition and detection under the application background of complex environments, YOLOv5 is prone to problems such as misrecognition and missing recognition. the improved YOLOv5 algorithm and image processing technology are combined to complete the identification and detection of gear missing teeth and cracks, and quantified the degree of gear damage to realize gear invalidation

judgement, so as to improve the automation of remanufacturing and disassembly of waste products.

2 Gear Defect Identification and Invalidation Judgement

Gears are key parts of waste products and high-value materials for remanufacturing. In the smart disassembly line for remanufacturing, the accuracy and speed of gear detection are crucial to subsequent disassembly. At present, there is no quantitative technical standard for gear defects. In order to realize the invalidation judgement of waste gears, the target detection algorithm based on YOLOv5 network model is used to establish a waste gear detection model to complete the detection and identification of different types of gears. The traditional image processing method is used for completing the multi-defect detection of waste gears and establish the detection model of broken teeth and cracks of gears, which realizes the invalidation judgement of waste gears (see Fig. 1).

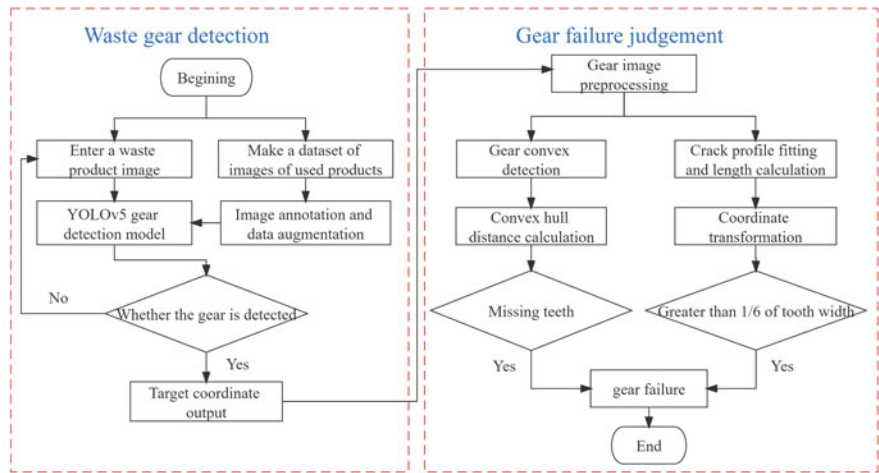
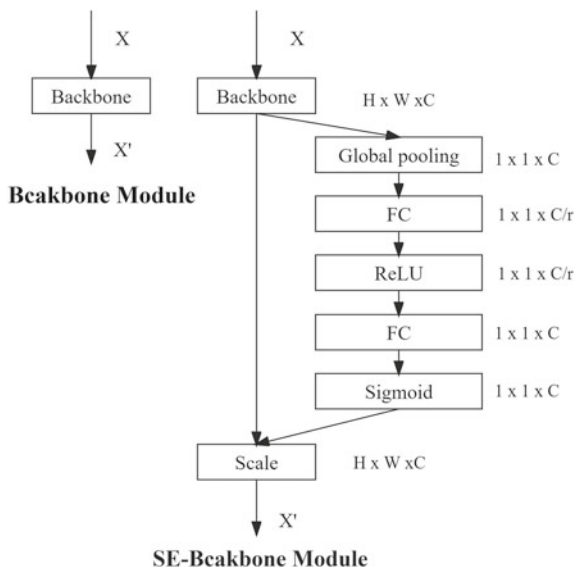


Fig. 1 Flow chart of gear invalidation judgement

Fig. 2 Introducing the SE module to backbone



3 Object Detection of Parts Based on Improved YOLOv5

3.1 Improvement of YOLOv5 Algorithm Model

The working principle of the SE module is shown in Fig. 2 [7]. adding the SE attention mechanism module to the Backbone module of YOLOv5(YOLOv5-SE), the recognition attention is focused on the target area, so as to obtain more target details and suppress useless information (see Fig. 2).

3.2 Parts Dataset and Model Training Environment

The 998 gear images that contain 2298 target gears are collected. These target gears are used as a data set, whcih is expanded through data enhancement processing methods to improve the detection accuracy and generalization ability of the model, such as image flipping, image rotation, brightness adjustment, etc..

The experiment is carried out on the AutoDL cloud server, based on Python language and PyTorch framework. The configuration is shown in Table 1.

The main training parameters in the network training process are as follows: The momentum parameter is 0.9, the weight decay coefficient is 0.005, the learning rate is 0.01, the batch size is 64, and a total of 300 epochs is trained. The test set loss trend of the improved YOLOv5 algorithm (loss-se) and the original YOLOv5 algorithm (loss) is recorded in Fig. 3 (see Fig. 3).

Table 1 Table of the experimental configuration parameters

Configuration	Type
Operating system	Windows 11
CPU	Intel(R) Xeon(R) Platinum 8255C CPU @ 2.50GHz
GPU	RTX 2080 Ti memory 11G
Python	3.8
PyTorch	1.11.0

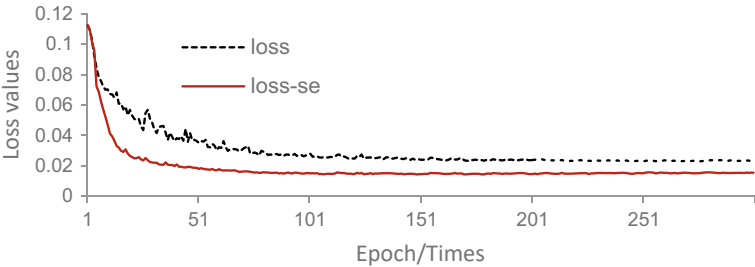


Fig. 3 Trend of loss values

In Fig. 3, The YOLOv5 model tends to be stable at the 125th epoch, where its loss value is around 0.023. Moreover, the YOLOv5-SE becomes steady at the 100th epoch, where the loss value is around 0.015. Comparing the two models, the loss value of YOLOv5-SE is reduced by 34.78%, and its model stabilizes faster. Therefore, the YOLOv5-SE model has more advantages in detection performance.

3.3 Analysis of Gear Recognition Results

The result of gear recognition of waste products is shown in Fig. 4, in which the block represents the target gear recognition box. Different sizes and multi-target gears can be effectively recognized in Fig. 4. These show that the gear recognition model has a good recognition effect (see Fig. 4).

In order to better evaluate the detection performance advantages of YOLOv5-SE, a data set, containing 100 gear images that has 179 gear targets is used to simultaneously establish YOLOv5 and YOLOv5-SE gear recognition network models. The test results are shown in Table 2.

In Table 2, Compared with the YOLOv5 model, the recognition rate of the YOLOv5-SE model is 95.50%, increasing by 7.69%. the error rate is 4.45%, reducing by 7.74%. In terms of recognition speed, the single recognition time of the YOLOv5-SE network structure is slightly higher than that of the YOLOv5 model, but the



Fig. 4 Gear recognition effect diagram

Table 2 Performance comparison of different methods

Algorithm	Correct detections	Missing detections	Accuracy	Error rate	Time/s
YOLOv5	157	22	87.81%	12.19%	0.334
YOLOv5-SE	171	8	95.50%	4.45%	0.358

difference is only 0.024 s, which meets the real-time detection requirements of the automatic disassembly line.

3.4 Gear Image Mask Processing

Target Gear Coordinate Output. For the purpose of reducing the background interference in the recognition process, the object boundary box in the target detection result is utilized to realize the target gear box selection and gains its position coordinates. After that image masking operation is used to eliminate the target gear background and improve the accuracy of gear defect recognition.

Taking Fig. 4a as an example, there are two gear targets in the figure, the large gear is recorded as number 1, the small gear is number 2, the center coordinates of each gear target detection frame are recorded as point O, and the coordinates of the upper left vertex are point P, so as to determine the gear target location. The specific coordinates are shown in Table 3.

Gear Mask Processing. The center and radius of the gear are obtained based on its coordinates and processed with a circular mask. all the background is shielded except the gear target, which reduces the interference of subsequent defect identification.

Table 3 Gear target detection frame coordinates

Gear number	Coordinate O	Coordinate P
1	(1671.0, 1115.5)	(683.0, 90.0)
2	(2769.0, 1660.5)	(2424.0, 1293.0)

4 Identification and Quantification Treatment of the Surface Defects of the Parts

The defects of the gear mainly include broken teeth, cracks, peeling and so on. Broken teeth and cracks have the greatest impact on the gear performance. We detect and quantify them by image processing technology, and complete the gear invalidation judgement with the gear invalidation evaluation criterion.

4.1 Identification of Gear Invalidation Defects

Image Preprocessing. In order to detect the gear image more conveniently, the target image is preprocessed, as shown in Fig. 5. By image gray, bilateral filtering and Otsu threshold processing, the gear contour information is extracted to obtain the gear contour image (see Fig. 5).

Gear Convex Hull Vertex Acquisition. The outer profile of the gear is a typical convex hull feature. The result of convex hull point acquisition is shown in Fig. 6 where the dotted line is the centerline of the gear profile. There are convex hull points with uniform distance distribution on the normal gear tooth contour, but the convex hull points cannot be detected in the tooth-missing part of the gear contour, and the distances between the surrounding convex hull points are scattered (see Fig. 6).

Gear Broken Teeth Detection and Result Analysis. In the process of convex hull vertex detection, it is easy to appear that one tooth top corresponds to multiple convex hull vertices, which affects the detection result. Compared with normal convex hull points, the distance between redundant convex hull points and its adjacent convex hull points is shorter, and redundant convex hull points can be filtered out by calculating the distance between each detected convex hull point. In Fig. 7, the 61 convex hull vertex coordinates are output, with the uppermost convex hull point on the center line of the gear contour as the first point. Part of the coordinate values obtained at intervals of four convex hull points in a clockwise direction are shown in Table 4.

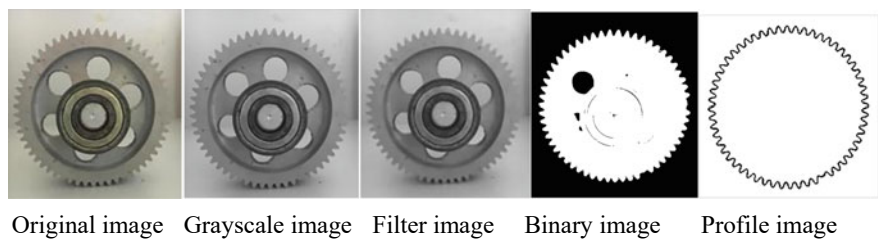


Fig. 5 Image preprocessing

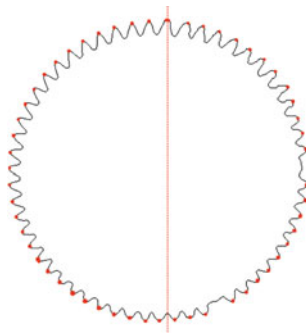


Fig. 6 Dated gear convex hull

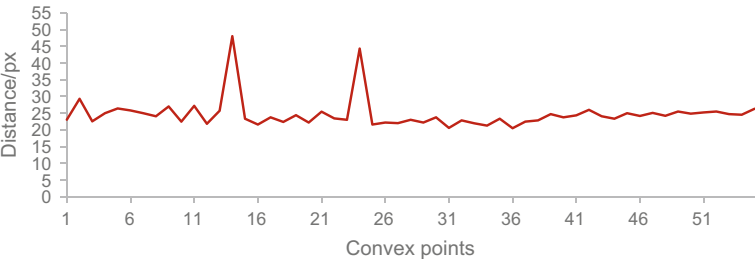


Fig. 7 Distribution plot of distance D values

Table 4 Partial convex hull vertex coordinates of the gear

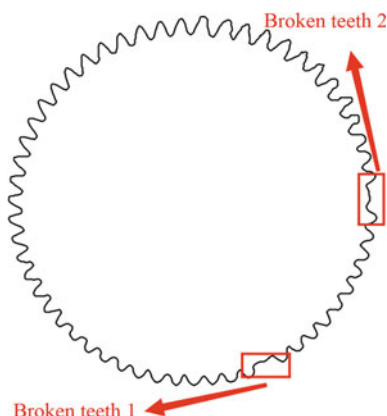
Number	Coordinate	Number	Coordinate	Number	Coordinate	Number	Coordinate
(1)	(249, 47)	(5)	(457, 287)	(9)	(174, 476)	(13)	(28, 215)
(2)	(329, 63)	(6)	(429, 373)	(10)	(114, 445)	(14)	(72, 128)
(3)	(395, 105)	(7)	(366, 444)	(11)	(64, 397)	(15)	(130, 78)
(4)	(444, 191)	(8)	(264, 484)	(12)	(26, 312)	(16)	(226, 49)

After obtaining the coordinates of the convex hull vertices, we calculate the distance between adjacent convex hull points, referred to as D . The position coordinates of a convex hull point is (X_i, Y_i) , and the adjacent convex hull point is (X_{i+1}, Y_{i+1}) .

$$D = \sqrt{(X_i - X_{i+1})^2 + (Y_i - Y_{i+1})^2} \tag{1}$$

Through the analysis, it is found that the normal value, referred to as D_z , fluctuates around the 25 pixel value, and the distance of the redundant convex hull points is much smaller than the $D_z/2$ pixel value, so the 12.5 pixel value is used as the threshold to remove the redundant convex hull points.

Fig. 8 Determination test results



After screening, the 55 convex hull vertex coordinates are obtained, calculating the distance between adjacent convex hull points, and the obtained value is drawn as a line graph (see Fig. 7).

In Fig. 7, the distance between adjacent convex points of normal gear teeth is similar, and its value is stable in the range of 20 to 30px. The distance between the 14th and 15th convex points and the distance between the 24th and 25th convex points are 48px and 44px respectively, which are out of the normal range, so it is judged that the gear has two broken teeth.

In Fig. 8, the convex points adjacent to the broken teeth are extracted, and the detected broken tooth parts are marked in the form of boxes. After gear convex hull point screening and broken teeth identification, the position of broken teeth of defective gears is successfully detected, which further proves the accuracy of algorithm detection (see Fig. 8).

4.2 Identification and Quantification of Gear Crack Defects

Gear Crack Extraction. Preprocessing operations such as grayscale processing and filtering processing can reduce the number of image channels and eliminate the interference of image noise, which is beneficial to subsequent image analysis and processing.

After image grayscale processing and filtering, the contrast between the gear crack information and the image background is not obvious, which is difficult to distinguish directly through threshold processing. Therefore, Histogram equalization processing is used to increase the overall grayscale range of the image. The grayscale range of the equalized image changes from [100, 255] to [0, 255], which disperses the image grayscale and significantly enhances the image crack information (see Fig. 9).

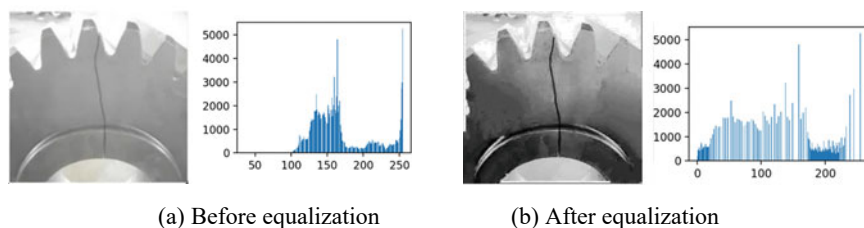


Fig. 9 Image equalization and the histogram

In order to reduce the interference of other information in the image, the image before and after equalization is differentially processed to highlight the difference of cracks, so that the binarization process extracts their contours. Figure 10a is a binary image without image difference processing, and Fig. 10b is a binary image after image difference processing. It can be seen from the two images that the redundant information of the image before difference processing is long line information, which is difficult to eliminate. The redundant information of the image after difference is short line or point information, which can be removed by filtering the contour length. The selected gear crack information is processed by opening operation to further eliminate other interference information. the obtained crack image is fitted with the outline of a rectangular frame to obtain the crack length (see Fig. 10).

Gear Crack Length Conversion Experiment. In order to obtain the actual length of the crack and complete the gear invalidation judgement, an image acquisition and ranging system is established, and the coordinate conversion is realized by image processing technology to match the actual length of the crack. The system consists of an adjustable tripod, a mobile phone and a laser rangefinder. The pixel of the mobile phone is 12 million, and the accuracy of the laser rangefinder is 1 mm.

The focal length of the mobile phone camera is obtained by the checkerboard calibration method, and 20 multi-angle 25×25 mm checkerboard images are taken. After calibration, the focal length of the camera is $f_x = 548.5675$, $f_y = 549.7411$.

$$W = \frac{L}{f} \times P \quad (2)$$

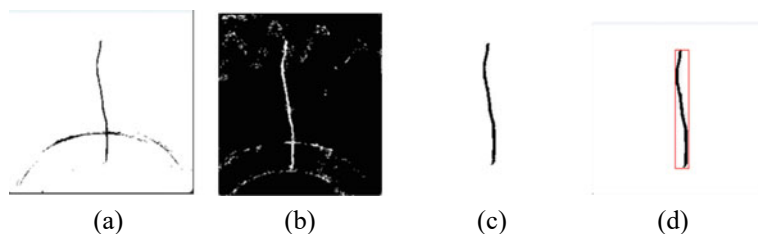


Fig. 10 Image differential processing and crack fitting

Table 5 Length and width information at different distances L

L/mm	P_x /pixel	P_y /pixel	L/mm	P_x /pixel	P_y /pixel
100	177.0	283.0	260	68.0	109.0
120	147.0	236.0	280	63.0	101.0
140	126.0	202.0	300	59.0	94.0
160	111.0	177.0	320	55.0	89.0
180	98.0	157.0	340	52.0	83.0
200	88.0	141.0	360	49.0	78.5
220	80.0	129.0	380	46.5	74.5
240	74.0	118.0	400	44.0	71.0

In the formula (2), L is the distance between the camera lens and the object, f is the focal length of the camera, W is the actual length of the object, and P is the pixel length of the object.

In the experiment, a cuboid iron block was selected as a reference object, the actual size of which was measured several times by a vernier caliper. By calculating the average value, the length of the reference object was finally obtained as 51.52 mm and the width was 32.24 mm, which were recorded as W_y and W_x respectively. During the experiment, the position of the camera was adjusted by moving the tripod up and down, and the moving distance of the camera was controlled by the laser rangefinder. At a distance of 100 to 400 mm from the reference object, a group of images is taken every 20 mm. There are 10 images in each group, and a total of 16 groups of images were taken, which were subjected to contour extraction and fitting processing to obtain the pixel length of the reference object.

The program gets the length and width information of the fitted image multiple times to obtain 16 groups of reference object size pixel information at different distances, which are denoted as P_x , P_y , as shown in Table 5.

We take the focal length and pixel distance as conditions, and substitute them into formulas (2) to obtain the conversion length of the reference object image, which are denoted as W_x' , W_y' . Finally, the image conversion length is compared with the actual measurement length to obtain the length recognition error.

In the range of 100 to 400 mm, the maximum error of the image conversion length of the reference object calculated by the formula is 0.56%, which proves the accuracy of the camera calibration experiment and coordinate transformation experiment.

5 Analysis of Parts Invalidation Judgement Results

For the broken teeth and crack defects of the gear, the evaluation criteria of the damage is shown in Table 6. If the gear has broken teeth or the crack length exceeds 1/6 of the tooth width, the gear is judged to be invalid.

Table 6 Gear invalidation evaluation criteria

Gear defect	Evaluation criterion	Maximum damage
Broken tooth	Whether the gear is broken	–
Crack	Crack length	No more than 1/6 of the tooth width

Based on the YOLOv5-SE detection model, the gear recognition is realized. Two gear images of different sizes are taken at a distance of 150 and 200 mm from the target object. The boxes in the figure represent the identified gear cracks and broken teeth defects, and the dotted line represents the gear centerline. According to Fig. 11a, the 2 cracks and 3 broken teeth were identified in the bull gear, where the left side of the center line is the 2 cracks and the right side is 3 broken teeth. In Fig. 11c, one crack and one broken tooth are identified on the pinion, where the box above the center line is the crack site and the box below is the broken tooth site (see Fig. 11).

The invalidation judgement results for bull gear and pinion are shown in Table 7. It can be seen from Table 7 that the lengths of the two crack defects identified in Fig. 11a are 3.94 mm and 10.15 mm respectively, and the identification errors are 1.3% and 0.6%. Among them, the crack length of 10.15 mm exceeds 1/6 of the tooth width. According to Table 6, the gear failed because it had a crack exceeding 1/6

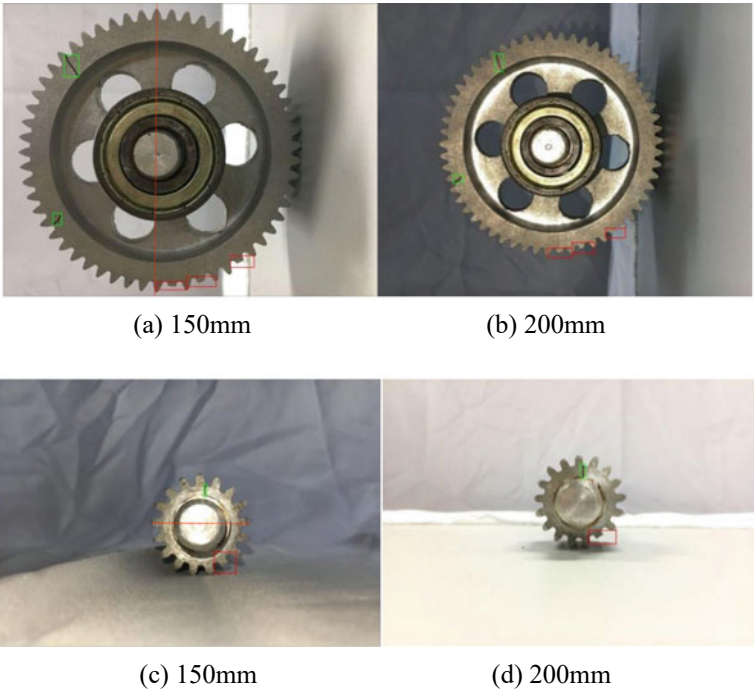


Fig. 11 Gear defect identification

Table 7 Gear invalidation judgement result

Serial number	Broken tooth/crack	Image length	Conversion length	Actual length	Tooth width	invalidation
(a)	3/2	14.41/37.2	3.94/10.15	3.99/10.21	27.92	Invalid
(b)	3/2	10. 81/27. 85	3.94/10.14	3.99/10.21	27.92	
(c)	1/1	13.02	3.55	3.60	29.47	Invalid
(d)	1/1	10.01	3.64	3.60	29.47	

of the tooth width and there was a broken tooth defect. In Fig. 11c, the length of a crack defect is 3.55 mm, which does not exceed 1/6 of the tooth width of the gear, but there is a broken tooth defect, so it can be judged that the gear is invalid.

6 Conclusion

- (1) The article improves the original YOLOv5 model by adding the SE attention mechanism, and has achieved good application results in the process of waste gear recognition. After comparison, the accuracy of the improved model detection is 7.69% higher than that of the original model, reaching 95.50%, which meets the production requirements of the remanufacturing automatic disassembly line.
- (2) The gear contour information is obtained by preprocessing and contour extraction operations on the image after removing the background interference. The convex hull information of the gear contour and the distance between each convex hull point are determined by convex hull vertex detection, which realizes effective and rapid identification and detection of gear broken teeth.
- (3) The crack information is identified by image processing technology, and the pixel length of the crack is obtained by contour fitting, which completes the conversion of the crack image length and the actual length. By quantifying the length of the gear crack, the length identification error does not exceed 1.38%, which realizes the accurate identification of the actual length of the gear crack.
- (4) Combining the improved YOLOv5 gear detection model with broken teeth and crack recognition methods, the problem of waste products affecting recognition accuracy is solved due to complex background interference. And the failure judgement of defective gears is realized fast and accurately.

Research on identifying defects in remanufactured product parts provides a theoretical basis for their disassembly automation. However, the article only inspected the defects of the gears and did not design other parts. Subsequent research can be expanded to study multiple types of parts and defects, achieving more accurate identification of component failure.

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Compact Convolutional Transformer for Bearing Remaining Useful Life Prediction



Zhongtian Jin, Chong Chen, Qingtao Liu, Aris Syntetos, and Ying Liu

Abstract An accurate prediction of bearing remaining useful life (RUL) has become increasingly important for equipment maintenance with the development of monitoring technology and deep learning (DL). Although Transformers are currently the most commonly used unique learning algorithms for sequential data, concerns about their computational efficiency and cost exist. In this regard, Compact Convolutional Transformers (CCT) have emerged as a promising alternative that employs sequence pooling and replaces patch embedding with convolutional embedding to enhance computational efficiency while maintaining high prediction accuracy with smaller model sizes. This study proposes an RUL prediction modeling approach that utilizes the Continuous Wavelet Transform (CWT) to transform time–frequency domain features into images, subsequently fed into CCT to establish a highly accurate prediction model for the RUL of bearings. This study conducted experiments using the XJTU-SY rolling bearing dataset. The performance was evaluated in terms of root mean square error (RMSE) and maximum absolute error (MAE) by modifying the layer configuration and comparing with other state-of-the-art algorithms.

Keywords Deep learning · Remaining useful life · Prognostic and health management · Transformer network

Z. Jin (✉) · Y. Liu

Department of Mechanical Engineering, School of Engineering, Cardiff University, Cardiff CF24 3AA, UK

e-mail: JinZ10@cardiff.ac.uk

C. Chen

Guangdong Provincial Key Laboratory of Cyber-Physical System, Guangdong University of Technology, Guangzhou 510006, China

Q. Liu

Key Laboratory of Road Construction Technology and Equipment of MOE, Chang'an University, Xi'an 710064, China

A. Syntetos

PARC Institute of Manufacturing Logistics and Inventory, Cardiff Business School, Cardiff University, Cardiff CF10 3EU, UK

1 Introduction

Due to its capability of handling high-dimensional data and automated feature extraction, DL has been extensively researched in the field of RUL prediction, and its excellent performance has been widely reported. Numerous RUL prediction solutions have been proposed for various industrial applications. Bearings are critical components in industrial production, and predictive maintenance can reduce downtime and minimize losses caused by unexpected failures. Therefore, accurate prediction of bearing RUL is necessary.

With advancements in deep learning, various novel DL methods and network structures have been introduced to enhance RUL prediction capabilities, including autoencoders, CNNs, LSTMs, attention mechanisms, and more. CNNs can aggregate local information but lack global pattern learning, while Transformer networks can capture long-term dependencies without distance limitations. However, Transformers are insensitive to local context and can be computationally expensive when processing long sequences. In computer vision, CCT is a smaller and more efficient version of ViT (Hassani et al. 2022), requiring less training time, data, and parameters while utilizing convolutional layers to aggregate local information. In RUL prediction, deep learning models heavily rely on large-scale training data. Insufficient data may hinder model performance.

In order to reduce computational costs and achieve accurate RUL prediction with smaller models, efforts were made to ensure effective data fitting within a more compact framework. This study proposes an RUL prediction modeling approach that utilizes the CWT to transform time–frequency domain features into images, subsequently fed into CCT to establish a highly accurate prediction model for the RUL of bearings. The experimental results using the XJTU-SY rolling bearing dataset demonstrate the merits of CCT over other state-of-the-art algorithms in terms of RMSE and MAE measures.

2 Literature Review

2.1 *The State-of-the-Art of RUL Prediction*

There are model-based and data-driven methods for RUL prediction. Traditional RUL prediction methods rely on prior knowledge for feature extraction, health indicator (HI) construction, and threshold setting, which are inefficient in the era of big data [3]. In practical applications, it is often challenging to establish accurate physical models for RUL estimation, especially when the fault propagation mechanisms are complex or not well understood [24]. Data-driven RUL prediction typically consists of three stages: data acquisition and preprocessing, feature extraction and computation, deep learning model training and RUL prediction. Bearing RUL estimation usually involves three types of features: time-domain features, frequency-domain

features, and time–frequency domain features [16]. Kamat et al. [10] extracted 22 time-domain features, but the selection is still necessary during model training to avoid overfitting if all features are used as input parameters. Deep learning models are implemented as network architectures composed of a stack of layers [9].

Convolutional layers in CNNs are capable of capturing local information from lower levels. For instance, [13] employed Short-Time Fourier Transform (STFT) to transform time series data into the time–frequency domain and utilized three convolutional layers with the same configuration to extract features, forming a multi-scale feature extraction model. Wavelet functions have also been combined with convolutional layer designs for feature extraction. Deng et al. [5] combined convolutional and LSTM techniques for bearing life prediction, achieving promising results. Li et al. [12] developed a novel wavelet-driven deep neural network called WaveletKernelNet (WKN), where a Continuous Wavelet Convolution (CWConv) layer was designed to replace the first convolutional layer of a standard CNN, enabling the first CWConv layer to discover more meaningful kernels. Convolutional layers have also been integrated with statistical methods for feature extraction. Huang et al. [7] employed a prediction model consisting of a deep convolutional neural network (DCNN) and a multilayer perceptron (MLP), embedding the developed dual network into the Bootstrap implementation framework. Yu et al. [22] also utilized DCNN and combined it with an improved Chicken Swarm Algorithm (ECSA) to develop a vision-based crack diagnosis method. This highlights the common usage of convolutional layers in aggregating local information at lower levels in the model establishment process.

LSTM is a type of recurrent neural network specifically designed for sequential inputs and is well-suited for regression-based sequence prediction tasks such as RUL [10]. Researchers have also developed variants of RUL prediction, such as the Bi-LSTM network proposed by Zhang et al. [23], which utilizes a bidirectional LSTM structure to achieve smoother predictions. Shah et al. [17] employed a bidirectional LSTM as the encoder and a unidirectional LSTM and fully connected layer as the decoder, resulting in a network that outputs a sequence of RUL estimates. This sequence-to-sequence LSTM encoder-decoder approach allows for sliding window reading of multidimensional time series in the input and output sequences, thereby improving the sample efficiency during training. Chen et al. [2] utilized LSTM networks and FCNN as two sub-networks for feature extraction, and the extracted features are then sent to a cascaded layer for fusion. This method leverages the advantages of LSTM networks and fully connected networks, enabling simultaneous processing of temporal and numerical data. Wang et al. [20] argued that purely data-driven methods overlook domain knowledge that governs the underlying degradation mechanisms. Therefore, they integrate deep neural networks (DNN) and LSTM models to characterize degradation processes in various engineering systems by fusing multiple sensor signals. Additionally, there are hybrid approaches involving other network architectures and feature extraction methods. Deutsch et al. [4] combined deep belief networks (DBN) with particle filters for RUL prediction, which falls under the category of purely data-driven methods.

From the state-of-the-art techniques in RUL prediction, it is evident that data-driven prediction methods are more convenient, and efficient, and have greater potential for development compared to traditional physics-based modelling approaches. The convolutional layers in CNNs are capable of capturing local information at lower levels, offering a cost-effective solution for feature extraction. Many studies have combined convolutional layers with other methods to extract comprehensive features. In this study, we first aggregate information using CWT and then utilize convolutional layers to discover more meaningful kernels.

2.2 *Studies of Transformers in PdM*

Since the introduction of “Attention is All You Need” by Vaswani et al. [19], Transformers have gained increasing popularity, and research based on attention mechanisms has been applied in various domains. Niu et al. [15] combined the encoder-decoder framework with the attention mechanism of memory networks, where the question, input, and output correspond to the query, keys, and values in a unified attention model. This approach has been applied in computer vision and natural language processing. Huang et al. [8] integrated CNN with Transformers and utilized a convolutional neural network with frequency Hoyer attention for predicting the remaining useful life of mechanical systems. They employed three Hoyer indices to demonstrate the advantages of incorporating attention mechanisms in RUL analysis from the frequency domain perspective. Wang et al. [21] employed a time convolutional neural network (TCN) with soft thresholding and attention mechanism for mechanical prediction. Multiple-channel sensor data were directly used as inputs to the prediction network, eliminating the need for feature extraction as a preprocessing step. In addition to the attention mechanism used in CNNs, another structure that can benefit from attention mechanisms is RNN. Chen et al. [3] embedded the attention mechanism into LSTM networks to help understand the importance of features and time steps.

Another feature of the Transformer is its encoder-decoder structure. Chen et al. [1] introduced a new Deep Convolutional AutoEncoder (DCAE) neural network based on quadratic functions. They introduced a new loss term by labeling the output of the encoder with quadratic functions in the DCAE’s loss function. Duan et al. [6] assigned weights to each time step information through an attention mechanism to highlight the embedding vectors of critical time steps. To reduce the decoding burden on individual embedding vectors, skip connections were introduced at each step of the decoding process to enhance the decoding capacity of the bi-directional gated recurrent units (BiGRU).

The introduction of attention mechanisms has been shown to enhance prediction accuracy in advanced techniques, but it also leads to a greater dependence of the model on big data. Complex models fail to achieve optimal performance when trained with limited data. Therefore, in this study, we attempt to incorporate the concept of

CCT from the field of computer vision into RUL prediction. This modelling approach is investigated to assess its effectiveness and performance.

3 Methodology

Firstly, the data is collected from the experiment platform. Secondly, the first prediction time (FPT) of the bearing is determined. Then, the time-domain data is processed into image data using CWT, and the resulting images are inputted into the CCT network for RUL prediction (Fig. 1).

3.1 FPT Determination

The FPT is a key element in the RUL prediction process, indicating the moment when the predictive model begins to generate estimates about the bearing’s RUL. Different approaches have been proposed to determine the FPT based on the condition monitoring data of the bearing, which can be affected by various factors such as the operating conditions of the bearing and the characteristics of the degradation process.

Previously, an alternative approach was proposed to determine the FPT. This method involved identifying the initial peak value that exceeded the 3σ interval and utilizing the corresponding time as the FPT. By employing this technique, early degradation indicators could be taken into account while minimizing false positives caused by random data fluctuations. These methodologies aim to effectively establish the FPT, thereby establishing a foundation for enhanced accuracy and efficiency in predicting RUL.

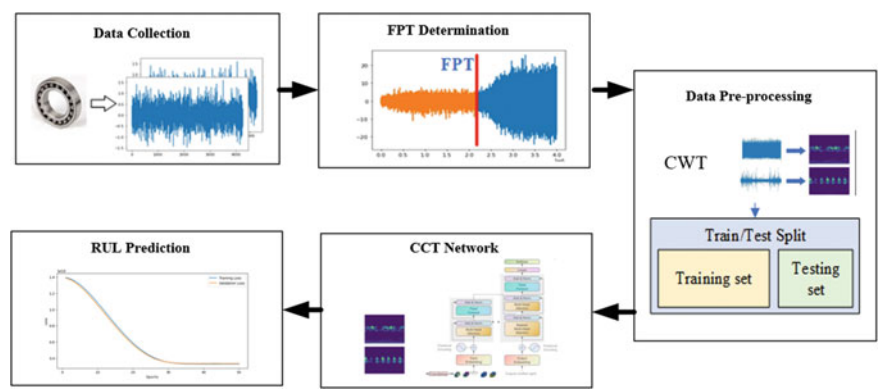


Fig. 1 The flow chart of the methodology

3.2 Data Pre-processing

The data pre-processing stage involves transforming the raw time-domain data into a format that can be used by the CCT model. This involves using the CWT to transform the time–frequency domain features into images. The CWT is a mathematical tool that can be used to analyze non-stationary signals, such as vibration signals from a bearing. By transforming these signals into images, we can capture both the time and frequency information of the signals, which can be useful for the prediction task. CWT's formula can be expressed as follows:

$$\text{CWT}(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

In the CWT, $x(t)$ is the input signal, a is the scale parameter, b is the translation parameter, and ψ^* is the complex conjugate of the wavelet function. The signal is convolved with the wavelet function through translation and scaling, resulting in a series of wavelet coefficients. Different scale and translation parameters generate wavelet responses with different frequencies and time-domain resolutions, enabling the analysis of the signal across different frequency ranges.

3.3 The Compact Convolutional Transformer Network

The network for this study is based on the CCT. The CCT is a type of Transformer model that has been designed to be more efficient and compact than traditional Transformer models. It achieves this by replacing the patch embedding used in traditional Transformer models with a convolutional embedding. This allows the CCT to aggregate local information from lower layers, which can help to improve the computational efficiency of the model. The CCT model is trained using the images generated from the CWT. The output of the CCT model is a prediction of the remaining useful life of the bearing.

The proposed model for RUL prediction uses a CCT architecture. It applies image data derived from the CWT of the bearing signals as input. The model comprises various layers, each contributing uniquely to the transformation and processing of the input.

The first layer, known as the Input Layer, receives the CWT image data from the bearing signals. Next, a Convolutional Embedding Layer replaces the conventional patch embedding found in Vision Transformers (ViT). This layer transforms the input image into a sequence of embedded vectors using convolution operations. At the core of the CCT model are the Transformer Encoder Layers. Each of these layers

incorporates a multi-head self-attention mechanism along with a position-wise feed-forward network. The number of these layers can be adjusted depending on the complexity of the model and the nature of the input data.

Finally, an Output Layer maps the output of the Transformer encoder to the desired format. In this particular model, it translates to a single value signifying the predicted RUL of the bearing. Detailed configuration of these layers, including the hyperparameters for the convolutional embedding and the number of Transformer encoder layers, will be determined and adjusted based on experimental results in the upcoming studies. This ensures an optimal performance of the CCT model for the task.

4 Case Study

4.1 Data Collection and Pre-processing

The data for this study comes from the XJTU-SY rolling bearing dataset. This dataset contains vibration signals from bearings operating under various conditions. 80% of the data was utilized for training purposes, while the remaining 20% was reserved for testing.

The raw time-domain data from the dataset is pre-processed using the CWT to generate images that can be used by the CCT model. This involves transforming the vibration signals into the time–frequency domain using the CWT and then converting these transformed signals into images.

4.2 Experimental and Model Setup

The CCT model is trained using the images generated from the CWT. The model is trained to predict the remaining useful life of the bearings based on these images. The parameters of the CCT model are set based on a series of preliminary experiments.

The performance of the CCT model is evaluated using two metrics: the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). These metrics provide a measure of the average error in the predictions made by the model (Fig. 2).

Here are the network hyperparameter settings:

- **Learning Rate:** A common choice is 0.001, but this could be adjusted based on the specific task and dataset.
- **Batch Size:** This depends on the memory capacity of the GPU used for training. A typical choice might be 32 or 64.
- **Number of Training Epochs:** This could be set to a high number (e.g., 100), and early stopping could be used to halt training when validation performance stops improving.
- **Optimizer:** Adam is a commonly used optimizer for Transformer models.

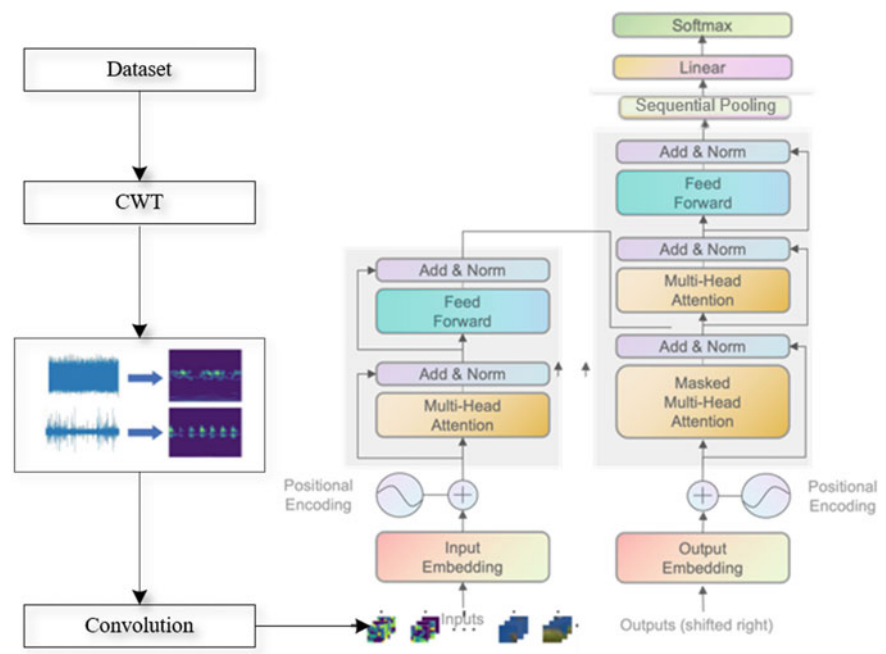


Fig. 2 Network structure

- Loss Function: Since this is a regression task, RMSE and MAE could be used as the loss function.

4.3 Experimental Results

Through training, our model’s mean squared error loss gradually decreases on the training set, indicating that the model progressively learns the relationship between vibration signals and the remaining bearing life. On the test set, our model achieves good prediction results with an average absolute error of around 20 min, surpassing other benchmark methods in terms of prediction accuracy (Fig. 3).

We further analyze the model and find that it often captures the trend of bearing condition changes. For example, as the bearing approaches failure, the model predicts a significant decrease in the remaining life. This suggests that the model learns the key features from the vibration signals and successfully applies them for remaining life prediction. However, there are also some errors in the model’s predictions. These errors may arise from data noise, model overfitting, incomplete extraction of vibration signal features, and other factors. In our future work, we will delve deeper into these issues and conduct more extensive research.

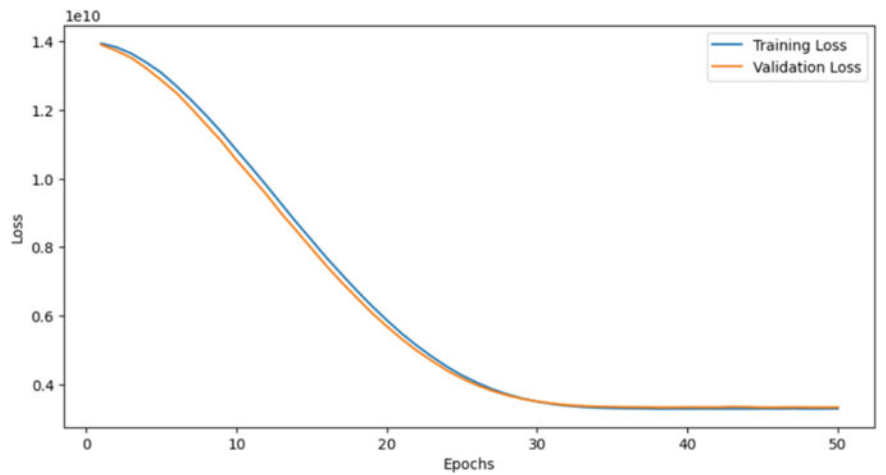


Fig. 3 Training loss and validation loss results

Next, we proceeded to modify the built-in layer configuration of CCT to investigate patterns and determine more suitable layer numbers. Figure 4 illustrates the RMSE and MAE results for four different layer configurations.

Figure 4 compares the relationship between different numbers of layers in CCT and their performance. For example, CCT-7/3 × 2 consists of 7 transformer encoder layers and a 2-layer convolutional tokenizer with a kernel size of 3 × 3. By comparing the results of the first two metrics, RMSE and MAE, it can be observed that increasing the number of transformer encoder layers can improve prediction performance under certain conditions. However, the comparison between the second and fourth items demonstrates that a higher number of Convolutional Tokenizers does not necessarily

Fig. 4 The comparison of the number of layers in CCT and its performance

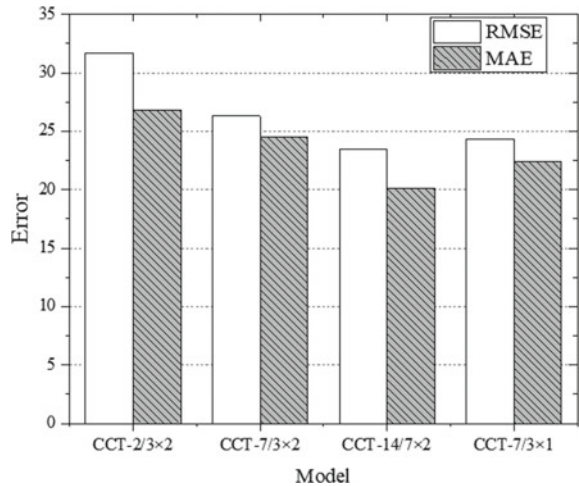


Table 1 The comparison of algorithm performance in terms of RMSE and MAE

Model	RMSE	MAE
CNN	30.2	25.4
LSTM	27.8	23.9
Transformer	26.1	22.7
Vision Transformer	24.3	21.4
CVT	24.0	21.2
CCT(Proposed)	23.5	20.1

lead to better results. The optimal performance is achieved in the third item, which involves larger transformer encoder layers and kernels. This can be partly attributed to the dataset being of moderate size, which requires more transformer encoder layers and larger kernels to enhance prediction accuracy.

After investigating the impact of modifying the built-in layer configuration on the model’s performance, we compared our model with other state-of-the-art algorithms, as shown in Table 1.

The comparison reveals that although CNN effectively captures low-level aggregated feature information, its predictive capability alone is relatively limited. LSTM, as an optimized version of RNN, exhibits higher predictive capacity compared to CNN. With the advancement of Transformer research, the integration of attention mechanisms and encoder-decoder structures has significantly improved prediction accuracy, offering a practical approach. However, the larger size of Transformer models often leads to suboptimal results when training data sets are limited. In contrast, the CCT incorporates attention mechanisms and encoder-decoder structures from Transformer and introduces further model simplifications.

When comparing CCT with VIT and CVT, it can be observed that VIT achieves higher prediction accuracy compared to the standard transformer due to its compatibility with CWT and global average pooling. On the other hand, CVT is a smaller version of VIT that utilizes sequential pooling, and its accuracy does not vary significantly compared to VIT. This could be attributed to the fact that the dataset used does not fall into the category of being extremely small or large, thus having a limited impact on the results. By incorporating convolutional layers in front of the CVT model, CCT effectively performs rapid dimensionality reduction in feature extraction. It can be considered an optimized version of VIT. Consequently, our proposed approach demonstrates superior performance based on the obtained results.

4.4 Discussion

Continuous wavelet functions and convolutional layers both demonstrate superior effectiveness in processing signals and extracting key features. However, in this approach, the time–frequency data is first transformed into image data using wavelet

functions and then further processed through convolutional layers for feature extraction. This two-step blurring process may result in a reduction of available information. Consequently, the model exhibits lower accuracy in the early stages of training, which is a common issue when transforming temporal information into image-based representations for feature extraction. This is an important consideration when utilizing feature extraction from images.

In future work, additional efforts may be required to improve the performance. This could involve further noise filtering or more powerful feature extraction techniques. Additionally, overfitting may be a concern, and regularization techniques or the design of more complex network structures could be explored to mitigate this issue.

On the other hand, this study solely utilized the XJTU-SY dataset, which limits the ability to fully explore the impact of varying dataset sizes on the outcomes obtained using the proposed approach. Therefore, future work can involve applying our method to datasets with different scales, potentially revealing more meaningful insights and comparisons.

5 Conclusion

In conclusion, this study demonstrates the effectiveness of the CCT for predicting the remaining useful life of bearings. By transforming the vibration signals from the bearings into images using the CWT, and then training the CCT model on these images, we are able to achieve high prediction accuracy with a smaller model size and lower computational cost. This approach has the potential to be a valuable tool for predictive maintenance in various industries.

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Surface Defect Detection of Remanufactured Products by Using the Improved YOLOv5



Weice Sun , Zhengqing Liu , Qiucheng Wang, and Bingbin Zhu

Abstract This paper presented a machine learning method to achieve accurate surface defect detection and classification of remanufactured products. An improved You Only Look Once (YOLO) network was proposed for training and testing an image detection model on a steel surface defect dataset. The results show that the proposed YOLO model has high accuracy in detecting surface defects for the remanufacturing quality detection, and the accuracy of the modified YOLO model was improved by 2.4% when compared to the original model in mAP0.5. Moreover, the improved model reasonably reduced the simulation calculation. The improved YOLO model has less operation, higher precision, and higher speed, which has practical application value in the surface defect detection of remanufactured products.

Keywords Remanufacturing · Machine learning · YOLO algorithm · Defect detection

1 Introduction

Remanufacturing is a resource-sustainable and environmentally friendly technology aimed at reprocessing and improving obsolete products or materials for reuse. However, the surface quality of obsolete products may be affected by factors such as wear, corrosion, and fatigue during the remanufacturing process. Therefore, accurate and comprehensive inspection of the surface quality of remanufactured products is crucial for defect localization, ensuring product quality, and enhancing reliability. Remanufacturing companies can ensure that remanufactured products meet or surpass the requirements of the original products in terms of performance, functionality, and appearance through the implementation of efficient surface quality

W. Sun · Z. Liu (✉)

College of Mechanical Engineering, Zhejiang University of Technology, Hangzhou 310023, China
e-mail: liuzhengqing@zjut.edu.cn

Z. Liu · B. Zhu

Zhejiang Jiuzhou New Energy Technology Co., Ltd., Taizhou 317523, China

inspection. Additionally, surface quality inspection can help remanufacturing companies determine appropriate remanufacturing methods and processes automatically and evaluate improvement and optimization strategies during the remanufacturing process.

Surface defects are one of the key concerns in the remanufacturing process [7, 8]. Traditional surface defect detection methods include manual visual inspection, magnifying glass observation, and magnetic particle testing. These methods can detect obvious defects such as cracks, fatigue damage, pores, and inclusions. However, for small defects or defects hidden beneath the surface, traditional methods may not be able to effectively detect them. In recent years, many advanced surface defect detection technologies have emerged, such as thermal infrared imaging, ultrasonic testing, eddy current testing, and X-ray testing. These technologies utilize specific physical properties such as heat, sound, electromagnetic, or radiation to non-destructively detect and evaluate surface defects.

The field of surface quality inspection in remanufacturing still faces some challenges and unresolved issues [4, 16]. Surface quality inspection of remanufactured products involves complex surface features and diverse materials, and the application of data analysis and intelligent algorithms is crucial for efficient and automated surface quality inspection. By utilizing technologies such as machine learning and artificial intelligence, automated defect detection, classification, and evaluation can be achieved.

3D scanning technology, by comparing the damaged model with the nominal model, has been widely used for defect detection. Y. He et al. [5] proposed an efficient two-step method based on an octree for accurate and rapid detection of remanufacturing defects, where the octree method is applied to create an effective topological structure of discrete points and perform Boolean operations to extract defects. L. Li et al. [11] proposed a reverse engineering-based method to assist in the remanufacturing process of worn parts. T. Liu [13] proposed a novel method for assessing the damage state of remanufacturing blanks by integrating magnetic and surface texture features. These detection methods often require specific equipment support or may be challenging to achieve automated detection without human involvement. Some scholars have proposed machine vision-based non-destructive defect detection methods, which have advantages such as automation, speed, and simplicity of equipment. J. K. Park et al. [17] proposed an automatic visual method for detecting surface part contaminants, scratches, burrs, and wear. L. Chen et al. [1] proposed a rapid surface defect recognition method for Directed Energy Deposition (DED). In situ, point cloud processing was developed using machine learning methods to achieve automatic surface monitoring without sensor intermittence. D. Tabernik et al. [20] presented a segmentation-based deep learning architecture specifically designed for surface anomaly detection and segmentation and demonstrated it in the specific domain of surface crack detection. Currently, remanufactured products mainly target metal parts, and methods for metal surface defect detection have been proposed. Y. He et al. [6] proposed a multi-level feature fusion network (MFN) that combines multiple hierarchical features into one feature for end-to-end steel surface defect detection. X. Lv et al. [15] proposed a novel end-to-end defect detection network

(EDDN) based on the Single Shot MultiBox Detector for deep metal surface defect detection.

YOLO (You Only Look Once) [18] is a real-time object detection algorithm that converts the object detection problem into a regression problem of a single neural network, enabling fast object detection. YOLO has been widely applied in various fields. W. Chen et al. [2] proposed a face detector called YOLO-face based on YOLOv3 to improve face detection performance. R. Gai et al. [3] proposed an improved YOLO-V4 deep learning algorithm for detecting cherry fruits. A. Kumar et al. [9] proposed an improved YOLO-V4 algorithm for mask detection. Y. Li et al. [12] proposed an improved RES-YOLO detection algorithm and applied it to automatic vehicle detection.

In this paper, the YOLOv5 algorithm was used to implement the detection of surface defects on remanufactured steel. Based on YOLOv5S, ASFF[19] (adaptively spatial feature fusion) and BIFPN [10] (bi-directional feature pyramid network) were incorporated to improve YOLOv5S and enhance defect detection accuracy. Our proposed visual inspection method is not only effective for surface quality inspection of remanufactured products but also applicable to other surface defects.

2 Method

2.1 The Original YOLO Architecture

As shown in Fig. 1, YOLO (You Only Look Once) divides the input image into a fixed-size grid and predicts multiple bounding boxes, confidence scores, and class probabilities for each grid cell. Each bounding box is represented by five values: the coordinates of the center point, width, height, and confidence. The class probabilities indicate the likelihood of the object within that bounding box belonging to different classes. By utilizing convolutional and fully connected layers, YOLO can simultaneously predict bounding boxes of different scales to capture objects of various sizes. Figure 2 depicts the original architecture of YOLOv5, which consists of three main components: backbone, neck, and head.

Backbone: The backbone is responsible for extracting high-level features from the input image. It typically consists of a series of convolutional layers or a pre-trained convolutional neural network (CNN) such as ResNet or EfficientNet. The backbone plays a crucial role in capturing and encoding the semantic information of the image.

Neck: The neck module is inserted between the backbone and the head. It is designed to further refine the features and enhance the spatial information by incorporating additional convolutional layers or feature fusion techniques. The neck module helps improve the performance of object detection by providing more discriminative and informative features.

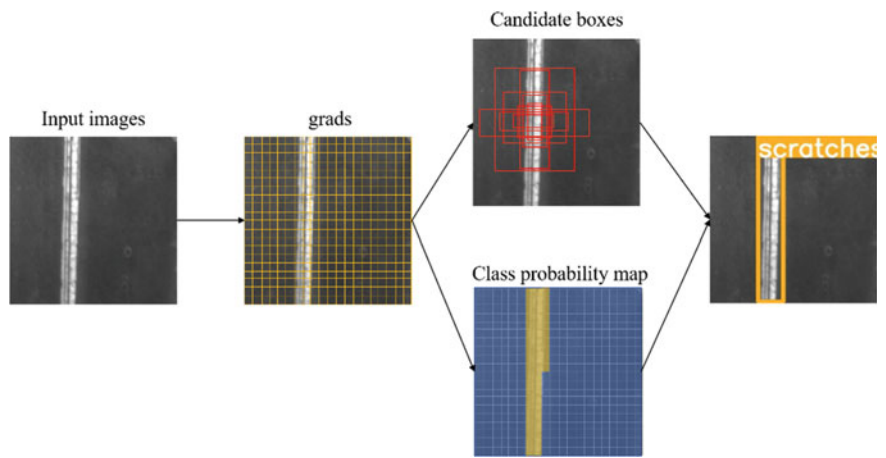


Fig. 1 YOLO object detection processing

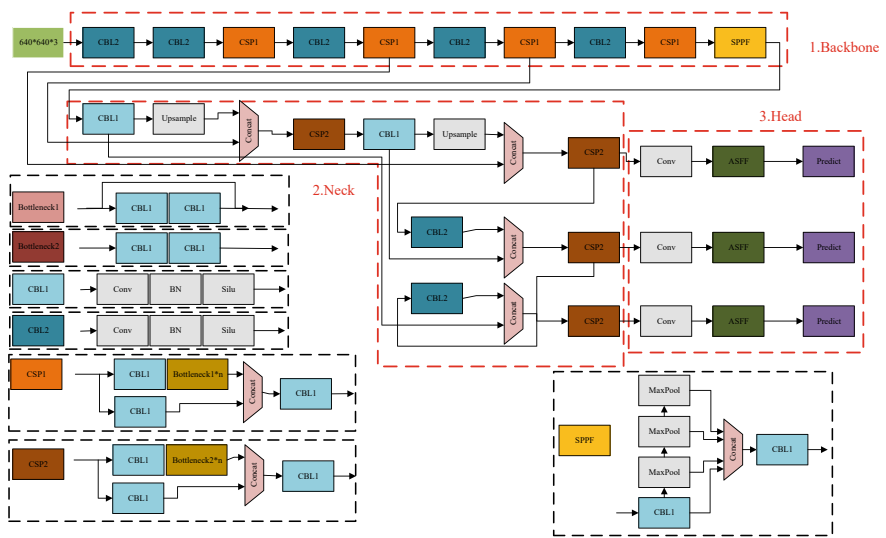


Fig. 2 The original YOLOV5

Head: The head is the final part of the YOLOV5 architecture and is responsible for generating the predictions. It consists of a series of convolutional and fully connected layers that transform the features from the backbone and neck into bounding box predictions, confidence scores, and class probabilities. The head predicts multiple bounding boxes at different scales and performs non-maximum suppression to output the final detection results.

Overall, the backbone extracts hierarchical features, the neck refines and combines these features, and the head generates the object detection predictions based on the fused features. This three-part architecture enables YOLOv5 to achieve accurate and efficient object detection performance.

2.2 ASFF

ASFF (Adaptive Spatial Feature Fusion) is a feature fusion method used in computer vision tasks. It aims to effectively fuse feature maps of multiple scales and adaptively learn weights for each spatial position to improve task performance. In traditional feature fusion methods, fixed weights or averaging operations are commonly used to merge feature maps of different scales. However, this approach overlooks the fact that different positions may contribute unequally to the task. Adaptive spatial feature fusion addresses this issue by introducing learnable weights, allowing the model to dynamically adjust the fusion weights based on the specific task and characteristics of the input data. The process involves Feature Resizing (up-sample and down-sample) followed by Adaptive Fusion, as illustrated in Fig. 3.

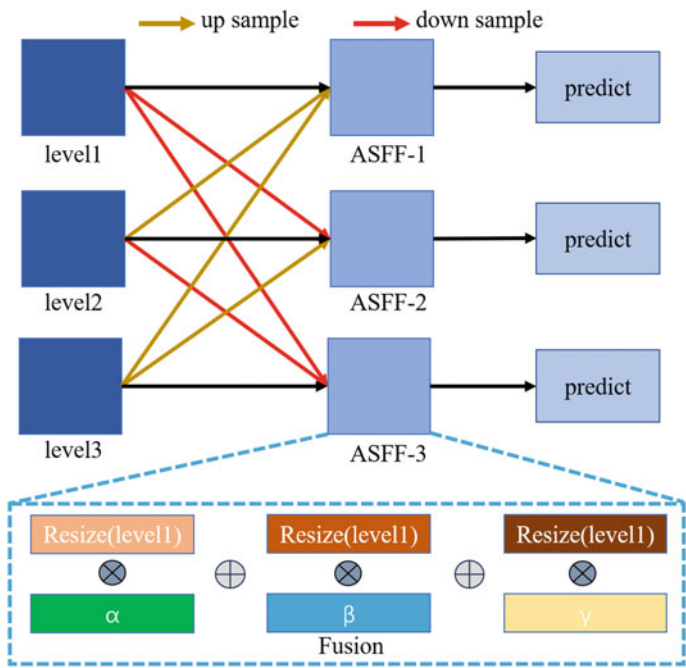


Fig. 3 ASFF module, α β γ is weight metric

2.3 BIFPN

BIFPN (Bi-directional Feature Pyramid Network) is a network architecture designed for object detection tasks, aiming to address the effective fusion and information propagation of multi-scale features. BIFPN is an extension of FPN (Feature Pyramid Network) that enhances the expressive power of the feature pyramid by introducing additional cross-level connections and backward pathways.

Weighted Feature Fusion is introduced in BIFPN, and a more efficient Fast normalized fusion method is utilized.

$$O = \sum_i \frac{w_i}{\epsilon + \sum_j w_j} \cdot I_i \quad (1)$$

where $w_i \geq 0$ is ensured by applying a Rectified Linear Unit (ReLU) after each w_i , and $\epsilon = 0.0001$ is a small value to avoid numerical instability. I_i is input.

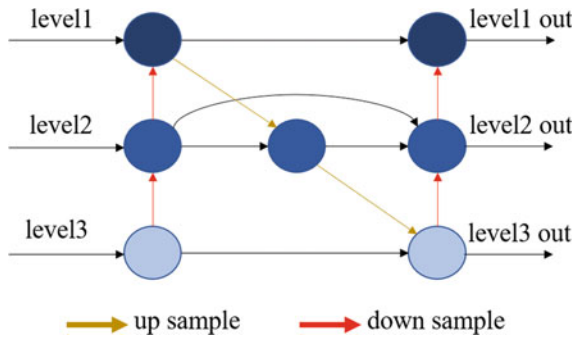
As a concrete example, here we describe the two fused features at level 2 for BIFPN shown in Fig. 4.

$$L_2^{td} = \text{Conv} \left(\frac{w_2 \cdot L_2^{in} + w_1 \cdot \text{Resize}(L_1^{in})}{w_1 + w_2 + \epsilon} \right) \quad (2)$$

$$L_2^{out} = \text{Conv} \left(\frac{w'_1 \cdot L_2^{in} + w'_2 \cdot L_2^{td} + w'_3 \cdot \text{Resize}(L_3^{out})}{w'_1 + w'_2 + w'_3 + \epsilon} \right) \quad (3)$$

where L_2^{td} is the intermediate feature at level 2 on the top-down pathway, and L_2^{out} is the output feature at level 2 on the bottom-up pathway. w_i and w'_i is weight. Resize indicates up-sampling or down-sampling. $\epsilon = 0.0001$ is a small value to avoid numerical instability.

Fig. 4 BIFPN architecture



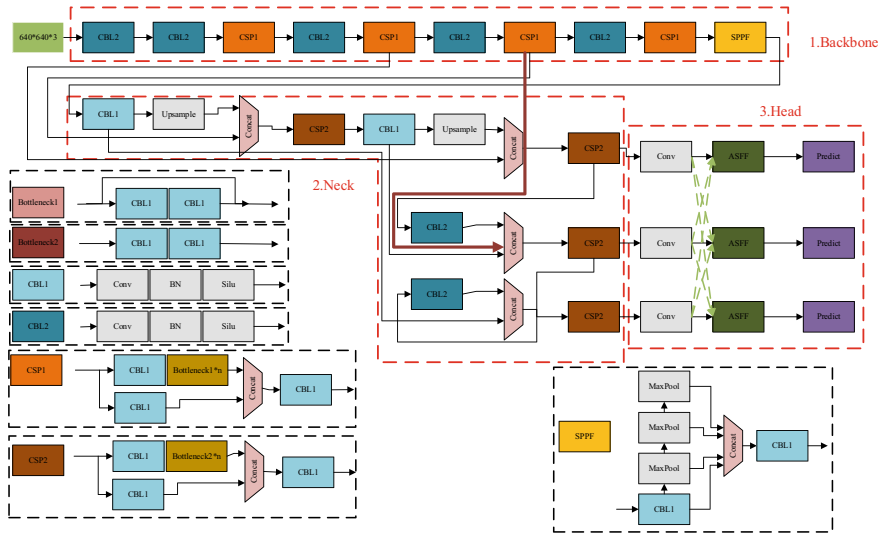


Fig. 5 ASFF-BIFPN-YOLO 5

2.4 ASFF-BIFPN-YOLO

By incorporating ASFF (Adaptive Spatial Feature Fusion) and BIFPN (Bi-directional Feature Pyramid Network) into the YOLO architecture, as shown in Fig. 5, a three-layer ASFF and BIFPN have been implemented, addressing multi-scale feature fusion and information propagation.

3 Experiment

We utilized the NEU Surface Defect Database [6] to characterize surface defects in the remanufacturing process. This dataset contains six typical surface defects found in hot-rolled strip steel: Rolled-in Scale (RS), Patches (Pa), Crazing (Cr), Pitted Surface (PS), Inclusion (In), and Scratches (Sc). The database includes 1800 grayscale images, with 300 samples for each of the six different types of surface defects. The original resolution of each image is 200×200 pixels.

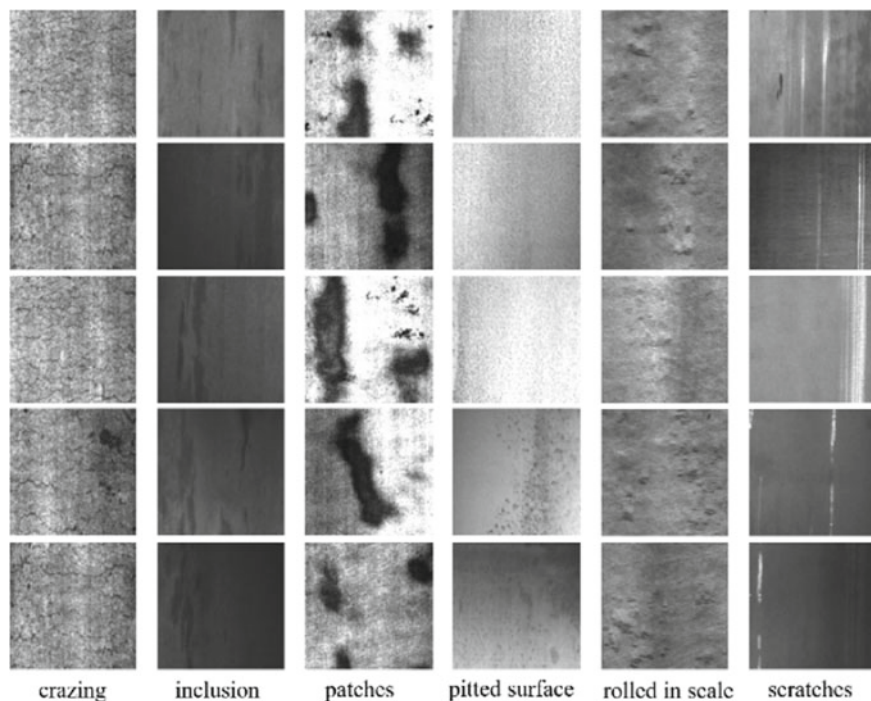


Fig. 6 NEU surface defect database

As shown in Fig. 6, we can observe significant variations within the same defect class in terms of appearance. For example, scratches (in the last column) can be horizontal, vertical, or inclined. Meanwhile, different defect classes share similarities in certain aspects, such as the scale of rolled-in defects, crazing, and pitted surfaces. Additionally, due to the influence of lighting conditions and material variations, the grayscale of defect images within the same class may vary.

In summary, the NEU Surface Defect Database faces two major challenges: significant appearance variations within the same defect class and similarities between different defect classes. Moreover, the defect images are influenced by lighting conditions and material variations.

In addition to using the SGD optimizer, we also tested the AdamW [14] optimizer and found that our proposed YOLO model showed improved convergence speed and accuracy when trained with the AdamW optimizer.

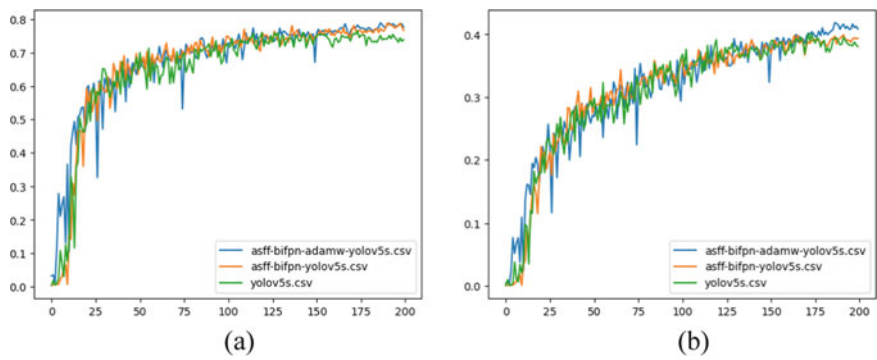


Fig. 7 mAP training curve **a** mAP 0.5 **b** mAP 0.5:0.95

We divided the dataset into a 90% training set (1620 samples) and a 10% test set (180 samples). We trained the models for 200 epochs using the following configurations: YOLOv5s, ASFF BIFPN CA YOLOv5s, and ASFF BIFPN CA AdamW YOLOv5s.

The mAP training curve is shown in Fig. 7, which indicates that our proposed improved model has a faster convergence speed and higher accuracy. The accuracy, recall, and PR curve of the model are shown in Fig. 8. Visually, it can be observed that our proposed improved model has a larger area under each curve, demonstrating better performance of the proposed improvement.

As shown in Fig. 9, a comparison reveals that our proposed detection algorithm accurately captures various defects. Additionally, it can be observed that our model also detects some defects that were not annotated in the real data. As shown in Table 1, the results show that the proposed model is effective, and it has a good potential in the application of defect recognition and diagnosis.

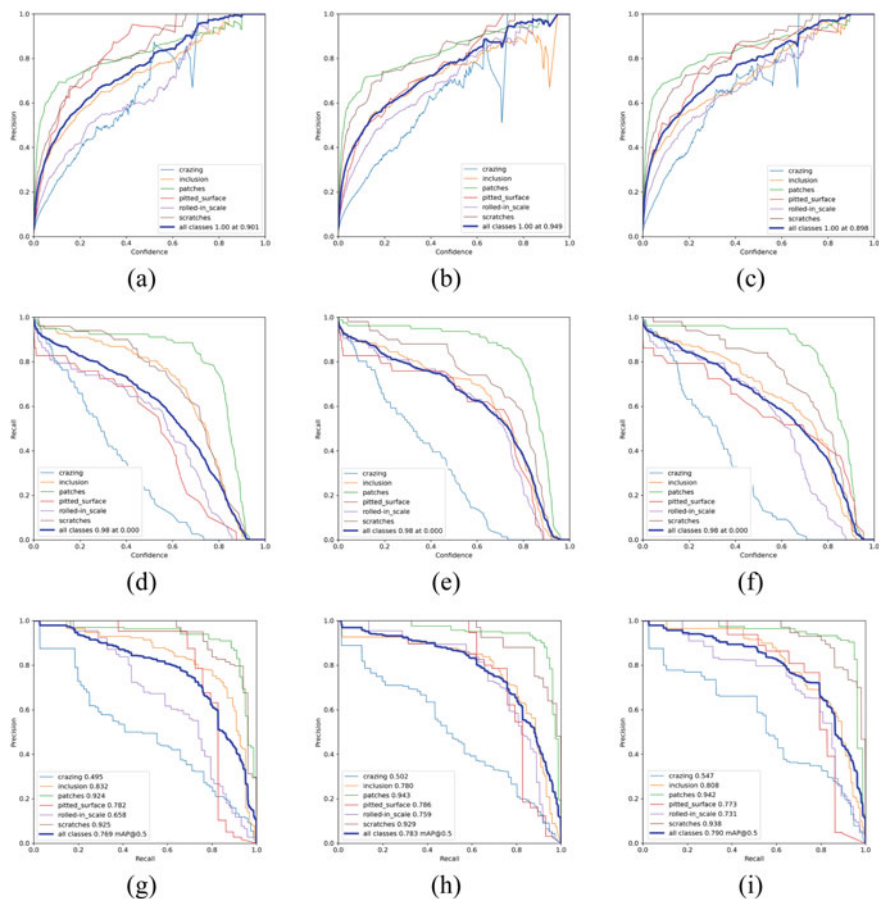


Fig. 8 **a** The P curve of yolov5s **b** The P curve of asff bifpn yolov5s **c** The P curve of asff bifpn adamw yolov5s **d** The R curve of yolov5s **e** The R curve of asff bifpn yolov5s **f** The R curve of asff bifpn adamw yolov5s **g** The PR curve of yolov5s **h** The PR curve of asff bifpn yolov5s **i** The PR curve of asff bifpn adamw yolov5s

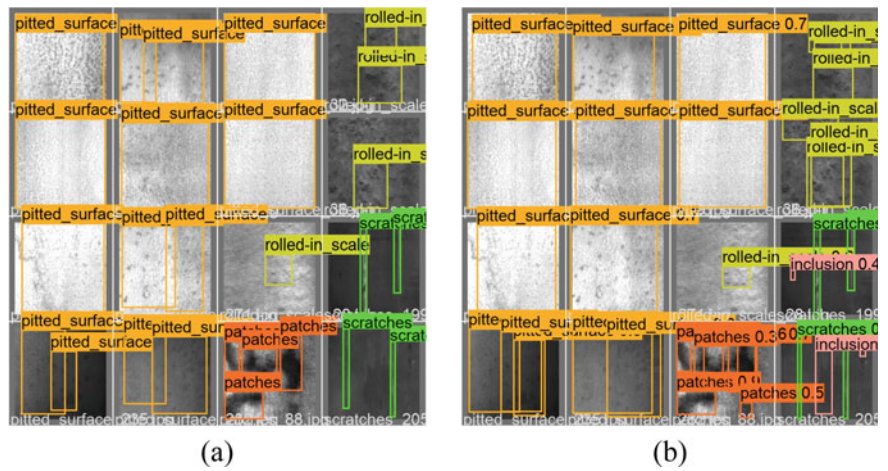


Fig. 9 a Label b prediction

Table 1 The highest mAP in the training process

	mAP0.5 (%)	mAP0.5:0.95 (%)
Yolov5s	76.6	39.0
Asff-bifpn-Yolov5s	78.9	39.9
Asff-bifpn-adamw-Yolov5s	79.0	41.8

4 Conclusion

In this paper, the Yolo algorithm was proposed for detecting surface defects on metal products in the re-manufacturing process. Our approach was validated by using a steel strip dataset. Additionally, an improved Yolo algorithm was proposed by incorporating ASFF (Adaptive Spatial Feature Fusion) and BIFPN (Bi-directional Feature Pyramid Network) into the YOLO architecture. The model was optimized using the AdamW optimizer and conducted relevant experiments. The experimental results demonstrate that compared to the original Yolov5 algorithm, our model (Asff-bifpn-Yolov5s) achieves a 2.3% improvement in mAP0.5 and a 0.9% improvement in mAP0.5:0.95. With the AdamW optimizer (Asff-bifpn-adamw-Yolov5s), the improvements are 2.4% and 2.8%, respectively. This confirms that our model exhibits better robustness.

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Knowledge Graph-Driven Manufacturing Resources Recommendation Method for Ship Pipe Manufacturing Workshop



Zijun Zhang, Sisi Tian, Ling Peng, Ruifang Li, and Wenjun Xu

Abstract In the context of the digitized and intellectualized transformation of ship pipe manufacturing enterprises, how to transform the massive multi-source heterogeneous data into knowledge and realize the reuse of manufacturing knowledge and experience in the ship pipe manufacturing workshop are the key to optimizing the allocation of workshop manufacturing resources. In order to solve the aforementioned issues, a knowledge graph-driven manufacturing resource recommendation method for ship pipe manufacturing workshops is proposed. Firstly, the correlation between multi-sources heterogeneous manufacturing data (device resources, manufacturing process of pipe, manufacturing orders) is analyzed and integrated. Then, a knowledge graph of manufacturing resources for the ship pipe manufacturing workshop is constructed. On this basis, a manufacturing resource recommendation method based on the Knowledge Graph Convolution Networks is proposed to recommend the device for orders in the ship pipe manufacturing workshop. Finally, a case study is implemented to verify the feasibility and effectiveness of the proposed method.

Keywords Knowledge graph · Ship pipe manufacturing workshop · Resource recommendation · Knowledge graph convolution networks

Z. Zhang (✉) · S. Tian · L. Peng · R. Li · W. Xu
School of Information Engineering, Wuhan University of Technology, Wuhan 430070, China
e-mail: zzj15@whut.edu.cn

Z. Zhang · S. Tian · R. Li · W. Xu
Hubei Key Laboratory of Broadband Wireless Communication and Sensor Networks, Wuhan University of Technology, Wuhan 430070, China

L. Peng
China Ship Development and Design Center, Wuhan 430064, China

1 Introduction

With the transformation and upgrading of the manufacturing industry, major ship-building countries around the world have accelerated their efforts toward advancing intelligent manufacturing. Ship pipe manufacturing is a vital element throughout the entire shipbuilding life cycle. The construction of an intelligent ship pipe manufacturing workshop (SPMW) holds paramount importance in the intelligent upgrading of shipyards. To adapt individual manufacturing orders, it is necessary to select resources from a wide range of manufacturing resources (MR). Traditionally, the ship pipes' production depends heavily on the experience of operators and the dependence often leads to the incorrect selection of MR, thus directly affecting the productivity of the SPMW and the overall quality of production. Therefore, selecting appropriate resources is crucial. Furthermore, the SPMW has accumulated extensive diverse data from multiple sources [1]. And it suffers from a lack of capacity to manage knowledge, which results in the underutilization of knowledge in the workshop. Therefore, there is a need to quickly and accurately recommend MR for manufacturing orders.

A knowledge graph [2] is a structured semantic knowledge base, which can more effectively represent the relationships between data than ontology [3]. Currently, knowledge graphs have emerged in the manufacturing field [4–6] to provide more valuable decision support by extracting knowledge and mining the semantic information from large amounts of industrial data. By applying the knowledge graph to SPMW, the relationship between orders and MR can be mined to recommend MR accurately.

Summarily, a knowledge graph of MR in SPMW is constructed to manage the production elements in the workshop. On this basis, a knowledge graph-driven MR recommendation method is proposed to achieve accurate recommendations of MR for manufacturing orders by mining the correlation relationship between data.

The rest of this paper is organized as follows: Sect. 2 reviews the related work on resource recommendations for SPWM. Section 3 presents the framework of the SPWM resource recommendation method based on knowledge graphs. Section 4 describes the Knowledge Graph Convolution Networks-based (KGCN) SPWM resource recommendation method in detail. Section 5 case study verifies the feasibility of the proposed approach. Finally, Sect. 6 concludes the paper and indicates future work.

2 Related Works

Currently, numerous researchers have studied knowledge modeling in the industrial workshop to reuse knowledge on the industrial workshop. Zhou et al. [7] developed a dynamic knowledge base for smart manufacturing that advances the self-reflection and self-improvement of manufacturing systems. Ye et al. [8] used cloud technology to develop a knowledge base for CNC machining processes, mapped the common

standard STEP-NC to OWL, and described process-related knowledge in a readable and understandable way. Zhang et al. [9] developed an ontology-based knowledge representation model for organizing and managing knowledge resources generated at various stages of the product life cycle. Compared with using ontology techniques, knowledge graphs have better performance. Ren et al. [4] proposed a framework for constructing a manufacturing knowledge graph that discovers and complements the implicit missing relationships in the knowledge graph to obtain a complete industrial knowledge graph. Zhou et al. [5] incorporated temporal features into knowledge graphs to enable mining and reasoning about implicit information with industrial time knowledge. Liu et al. [6] developed multilayer manufacturing knowledge graphs to merge multidimensional, heterogeneous data in manufacturing processes, including time series data.

Collaborative filtering and content-based are currently the most prevalent resource recommendation methods [10]. Collaborative filtering emphasizes the similarities between users and items, while content-based methods emphasize the items' features and attributes. Valdiviezo-Díaz et al. [11] proposed a collaborative filtering method based on users and items by using similar information about users and items for recommendation. Son et al. [12] proposed a novel method based on content filtering which recommends by using a multi-attribute network to include all attributes in relevance calculation. Recently, recommendation systems have incorporated knowledge graphs for improved recommendation performance. Duan et al. [13] utilized a metal-cutting process knowledge graph and applied the personalized PageRank algorithm to recommend cutting tools for process planning. Deep neural networks are also used in recommendation systems. Li et al. [14] proposed a deep neural network-based manufacturing resource recommendation method to achieve fast matching of manufacturing tasks and MR by mining the relationship between them. Wang et al. [15] proposed KGCN, which utilizes structural and semantic information within the graph to capture user interests for recommendation.

Currently, there is much research on the construction of knowledge graphs in industrial workshops, but the knowledge modelling research specific to the SPMW is yet to be investigated. The manufacturing process in the SPMW is inherently resource-rich and complex, making it challenging for existing recommendation methods to mine the knowledge and experience of the SPMW. So, a knowledge graph-based recommendation method for MR based on the KGCN algorithm is proposed to fully utilize the comprehensive information contained in the knowledge graph.

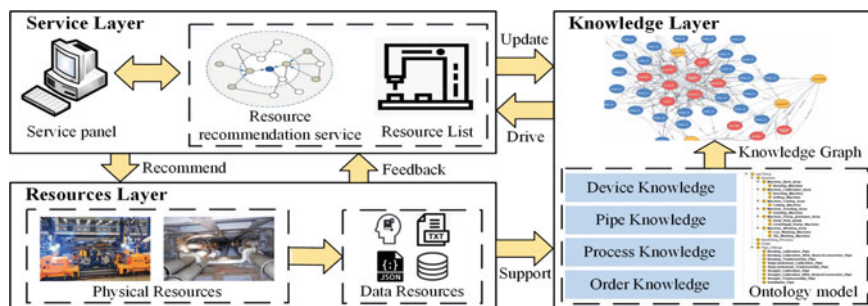


Fig. 1 Knowledge graph-based recommendation framework for SPMW

3 Knowledge Graph-Based Recommendation Framework

3.1 Knowledge Graph-Based Recommendation Framework for SPMW

A knowledge-driven framework for recommending MR on the SPMW is proposed, as shown in Fig. 1, and the framework consists of a resource layer, a knowledge layer, and a service layer.

The resource layer comprises physical and data resources. The physical resources in the SPMW include pipe fittings and devices such as cutting machines, and welding machines. The data resources include various types of data, such as device parameter data, process documentation, historical order data, pipe data, and expert experience.

The knowledge layer consists of the ontology model and knowledge graph. The ontology model is a unified knowledge description of SPMW, constructed based on ontology by analyzing various elements and extracting entities and relationships of MR in the resource layer. Based on the ontology mode, a knowledge graph of the MR is built.

The service layer primarily offers manufacturing resource recommendation services to recommend appropriate devices for manufacturing orders and provides support for the knowledge acquisition requirements of SPMW.

The resource layer provides data support for the knowledge layer. The manufacturing knowledge formed by the knowledge layer drives the resource recommendation of the service layer. After the iterative recommendation and operation optimization of the resource layer, the knowledge is updated.

3.2 Knowledge Modeling for SPMW

A knowledge graph is developed to model and reuse the SPMW knowledge. Firstly, an ontology model is structured to represent the manufacturing knowledge in the

SPMW. Then, under the guidance of the ontology model, knowledge is extracted from data sources to establish a knowledge graph of the SPMW.

Ontology model construction. A manufacturing resource ontology model was created to describe the MR utilized in the production of ship pipes. This model includes four sub-ontologies, namely device, order, pipes, and process sub-ontologies to identify and categorize specific aspects of the pipes manufacturing process.

Device sub-ontologies. The device sub-ontology contains device basic information (such as device ID, manufacturer, model, and location), and device processing capability, as shown in Eq. (1).

$$device = \{BasicInfo, Processing\ Capability\} \quad (1)$$

The processing capacity of a device reflects its performance and processing range. The processing capacity includes the material of processed pipes, cutting accuracy, bending speed, etc. It should be noted that different types of devices are associated with different performance parameters. For instance, a cutting machine is primarily judged based on cutting accuracy, whereas pipe bending machines are evaluated based on bending accuracy.

Order sub-ontologies. The order sub-ontology defines manufacturing orders. It contains basic order information, manufacturing requirements, and device list, as shown in Eq. (2).

$$order = \{BasicInfo, Processing\ Requirements, Device\ List\} \quad (2)$$

Basic order information includes essential details such as order ID, customer information, notes, and time of delivery. Manufacturing requirements refer to the order's technical specifications, such as pipe information, process requirements, precision requirements, etc. The device list is comprised of all necessary devices to complete every process of the order.

Pipes sub-ontologies. The pipes sub-ontology describes the physical parameters of the pipes in the workshop and classifies them according to types such as bends, straight pipes, straight pipes with branches, etc. The physical parameters are shown in Eq. (3), including the number of the fitting, the material of the fitting, etc.

$$pipes = \{Pipe_{ID}, Pipe_{Type}, Pipe_{Material}, Pipe_{Size}, \dots\} \quad (3)$$

Process sub-ontologies. The process sub-ontology describes the processing procedure of pipes in the SPMW, incorporating process number, process code, process type, process description, process content, and other relevant data, as shown in Eq. (4).

$$process = \{Process_{ID}, Process_{Code}, Process_{Type}, Process_{Content} \dots\} \quad (4)$$

Knowledge graph construction. Workshop knowledge is transformed into a structured MR knowledge graph of SPMW through three critical steps: knowledge extraction, knowledge update, and knowledge storage, as shown in Fig. 2.

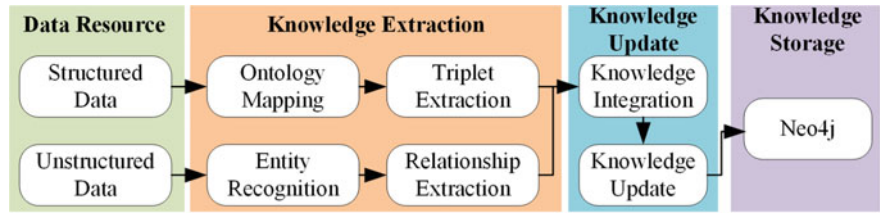


Fig. 2 Knowledge graph construction process

Data resources in the SPMW include structured data and unstructured data. Order data, pipe fitting data, and processing process data are structured data. Device manuals, device logs, and work instructions are unstructured data.

The purpose of knowledge extraction is to extract information including entities, attributes, and relationships from the data resources. For structured data, the D2R tool is used to transform the data into RDF triples. For unstructured data, natural language processing technology is used to recognize entities and attributes and extract the relationships.

Due to the temporal nature of data and the possibility of new information, knowledge obtained through extraction is integrated with existing knowledge, and the accuracy and currency of knowledge need to be guaranteed through knowledge updating.

Finally, the extracted information will be stored in Neo4j [16] in the form of a knowledge graph, as shown in Fig. 3, the blue node represents the order, the green node represents the device, the yellow node represents the pipes, the pink node represents the machining process, and the red node represents the attribute value.

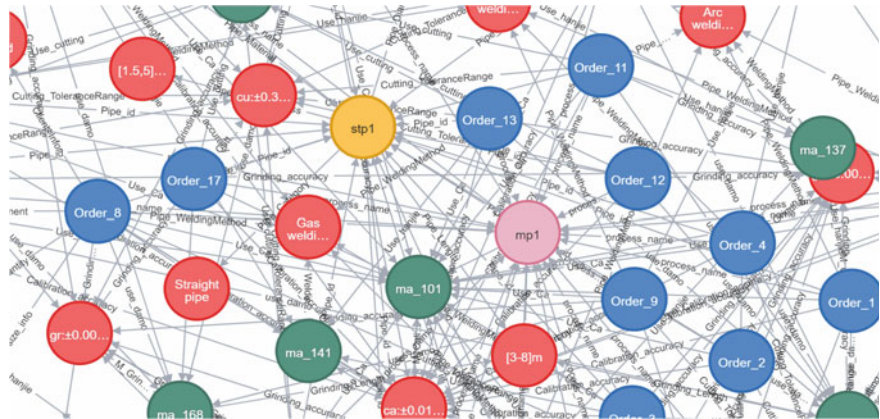


Fig. 3 Knowledge graph of MR in SPMW

4 MR Recommendation Method for SPMW Based on KGCN

Upon receiving an order for pipe processing, the workshop selects suitable devices promptly to complete the order. Hence, it requires an efficient device recommendation method that ensures efficient processing. KGCN [15] is an efficient recommendation algorithm that uses the structural and semantic information in the knowledge graph to improve recommendation accuracy. KGCN can link the order's manufacturing requirements to the MR to recommend appropriate MR quickly and accurately. Based on this, an MR recommendation method based on KGCN is proposed.

The overall flow of the proposed method as shown in Fig. 4, includes two main parts, order information extraction and device recommendation. Through information extraction, manufacturing orders are added to the MR knowledge graph and an order subgraph is generated as KGCN layer input. After information aggregation through the K-layer KGCN layer, the order entity contains rich information, which can be used to predict the matching degree of device. The device for each process is recommended based on predicted scores and forming a group of machines to complete all processes of pipe processing. Finally, the MR knowledge graph is updated.

4.1 KGCN Layer

The KGCN Layer extracts valid information from the knowledge graph and uses it to make predictions about how well the manufacturing order matches the device, based on the extracted information. By combining the order-device interaction matrix extracted from the MR knowledge graph, its parameters can be trained for improved prediction results. Specifically, the knowledge graph is a weighted graph where the relationship weight represents the device's degree of preference for that relationship. For example, the machining accuracy relationship in an order is even more important for devices because it depends on whether the device is capable of processing that order. π_r'' is the device-relation score, as shown in Eq. (5).

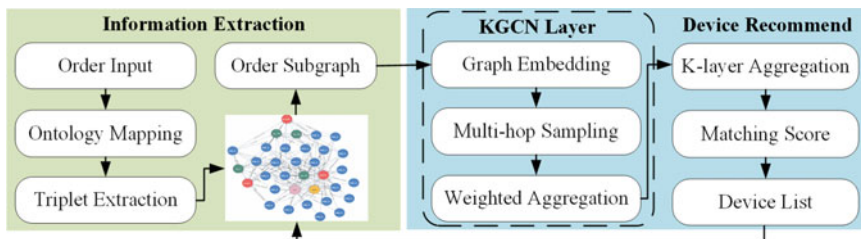


Fig. 4 MR recommendation method based on KGCN

$$\pi_r^u = g(r, u) \quad (5)$$

where u represents the device vector, r is the relationship vector, and g is a function, as the inner product. To aggregate information from surrounding nodes to the central node, a weighted sum of the neighboring nodes is necessary, as shown in Eq. (6).

$$v_{N(v)}^u = \sum_{e \in N(v)} \tilde{\pi}_{r_{v,e}}^u e \quad (6)$$

where $N(v)$ is the set of entities connected to the order v , $\tilde{\pi}_{r_{v,e}}^u$ is the normalized device-relation score, and $v_{N(v)}^u$ is a linear combination of v 's neighborhoods. $\tilde{\pi}_{r_{v,e}}^u$ is calculated in Eq. (7).

$$\tilde{\pi}_{r_{v,e}}^u = \exp(\pi_{r_{v,e}}^u) / \sum_{e \in N(v)} \exp(\pi_{r_{v,e}}^u) \quad (7)$$

Each node has a varied number of neighbors, and a high volume of neighboring nodes can intensify computational pressure. Thus, a hyperparameter k is defined to represent that only k neighbors are included in the computation for each node v . The neighborhood of node v is denoted as $S(v)$, and it satisfies Eq. (8)

$$S(v) \rightarrow \{e | e \in N(v)\}, |S(v)| = K \quad (8)$$

Finally, another message aggregation is performed, combining the vector v with its neighborhood representation $v_{S(v)}^u$, as shown in Eq. (9).

$$V' = \sigma(W \cdot \text{agg}(v, v_{S(v)}^u) + b) \quad (9)$$

where W and b are the transformed weights and deviations, and σ is a nonlinear function. Finally, V' is the order vector obtained by aggregation. There are three aggregation methods available, namely summation aggregation, contact aggregation, and neighbor aggregation, as shown in Eqs. (10, 11, and 12).

- Summation aggregator performs the operation of summing two vectors.

$$\text{agg}_{\text{sum}} = v + v_{S(v)}^u \quad (10)$$

- Contact aggregator performs the operation of concatenating two vectors.

$$\text{agg}_{\text{concat}} = \text{concat}(v, v_{S(v)}^u) \quad (11)$$

- Neighbor aggregators directly take the neighborhood representation as output.

$$\text{agg}_{\text{neighbor}} = v_{S(v)}^u \quad (12)$$

4.2 Device Recommendation

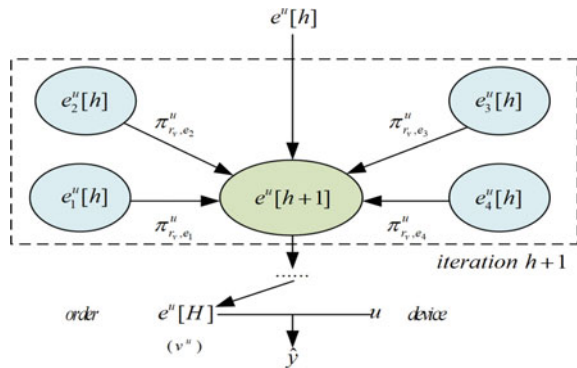
Through a single KGCN layer, the representation of an entity depends on itself and its direct neighbors, which is called a 1-order entity representation. Expanding the KGCN from one layer to multiple layers allows the entity representation to contain more information for reasonable prediction. The 0-order representation of each entity is propagated to the other resulting in a first-order entity representation, and the process is repeated to further propagate and aggregate to obtain a 2nd-order representation. The process of one iteration is depicted in Fig. 5, where $e^u[h]$ and its neighborhood representation are mixed to form the representation $e^u[h]$ for the next iteration.

The final representation of the entity contains extensive contextual information, and this representation relates to information about itself and its neighbor nodes. Specifically, the order vector contains information about the order's manufacturing requirements, pipe data, etc. Then the device's preference for orders is predicted.

$$y' = f(u, v^u) \quad (13)$$

In Eq. (13), u denotes the device vector, v denotes the order vector after the gathering information, and f is an arbitrary function such as the inner product. y' is the matching value, which indicates how well the order matches the device. The recommended set of devices for each process is sorted in ascending order based on their respective matching values. Ultimately, the recommended device group contains all the devices needed to produce all processes of the pipes.

Fig. 5 The calculation process of the prediction function



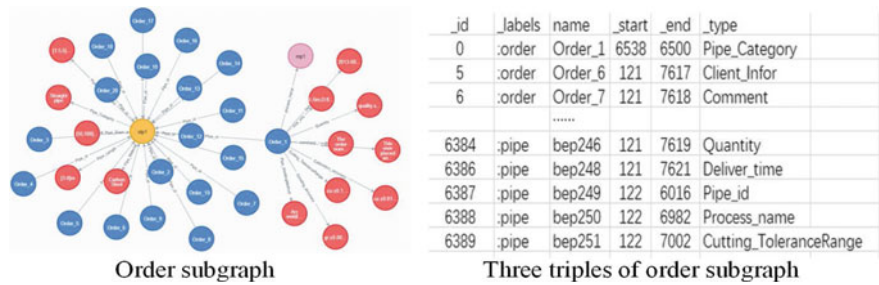


Fig. 6 The order subgraph (partial)

5 Case Study and Performance Analysis

This case study is based on the pipe manufacturing order in SPMW. There are several manufacturing device resources, including cutting machines, pipe bending machines, pipe calibrating machines, welding machines, drilling machines, grinding machines, etc. The pipe manufacturing orders in the workshop contain the manufacturing requirements and devices used for manufacturing.

5.1 Datasets

The dataset that is used in the experiment comprises two parts, namely the order subgraph and the device order interaction information, both of which are produced by the manufacturing resource knowledge graph. As shown in Fig. 6, the order subgraph is exported as three triples for easy processing, containing order information, process information, and information about the pipe to be processed. A label of 1 in the device order interaction file indicates that the order interacts with the device, and 0 indicates no interaction. The basic data parameters of the dataset are shown in Table 1.

5.2 Algorithm Performance Evaluation

To verify the effectiveness of the proposed method, singular value decomposition (SVD) [17] and RippleNet algorithm [18] are taken as the comparative baseline approaches. SVD is a matrix decomposition technique that recommends items based on the similarity calculation between user and item vectors, without knowledge graphs. The RippleNet is a graph neural network that uses user preferences to provide recommendations. The MR dataset is divided into training, evaluation, and test sets in the ratio of 6:2:2, with AUC, F1 and Recall [19] being utilized as performance

Table 1 Basic statistics and hyper-parameter settings for the dataset

Parameter	Value	Description
#Device	206	Number of devices
#Order	6000	Number of orders
#Interactions	57,180	Number of interactions
#Entities	37,030	Number of entities
#Relations	24	Number of relations
#KG triples	77,056	Number of triples
k	6	Neighbor sampling size
d	16	Dimension of embeddings
H	1	Depth of receptive field
λ	1×10^{-7}	l2 regularizer weight
η	2×10^{-2}	Learning rate
B	1024	Batch size

evaluation metrics while averaging the results from five repetitions of each experiment. For KGCN, the g and f functions are set as inner products, while σ is set as ReLU for the non-last layer aggregator and tanh for the last layer aggregator, and other hyperparameters are shown in Table 1. For SVD, the hyperparameters are set as follows: $d = 8$, $\eta = 0.5$. For RippleNet, the hyperparameters are set as follows: $d = 16$, $H = 3$, $\lambda =$, $\eta = 0.02$. The other hyperparameters are the same as those reported in the original paper.

The experimental results are shown in Table 2 and Fig. 7. It is concluded that the proposed method is effective and performs well. The performance of the KGCN and RippleNet models was better than that of the SVD model without KG. These results suggest that incorporating KG can effectively improve recommendation performance. In addition, the low recall in Top-K is probably due to the concentrated use of a certain device in the workshop.

Table 2 The results of AUC and F1 in CTR prediction

Model	AUC	F1
SVD	0.524	0.687
RippleNet	0.707	0.661
KGCN-sum	0.972	0.908
KGCN-concat	0.976	0.915
KGCN-neighbor	0.969	0.904
KGCN-avg	0.969	0.903

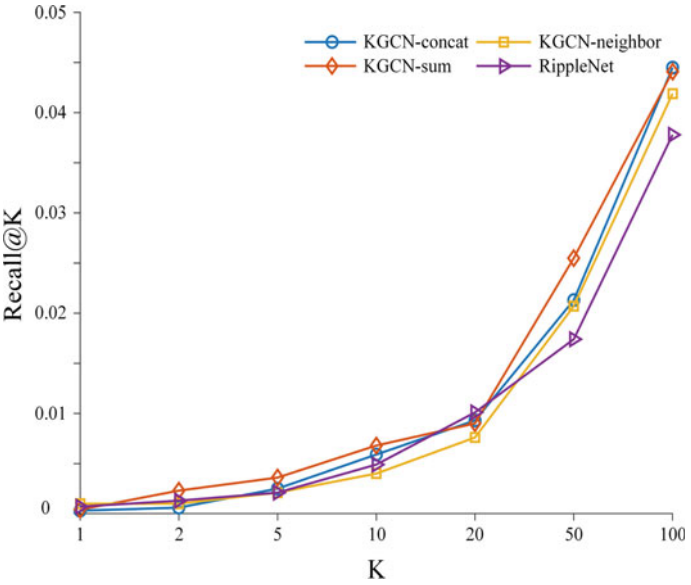


Fig. 7 The results of Recall@K in top-K recommendation

Table 3 Impact of neighbor sampling size

K	2	4	6	8	16
AUC	0.9695	0.9694	0.9715	0.9694	0.9687
F1	0.9095	0.8993	0.9067	0.9010	0.9007

5.3 Analysis of Hyperparametric

The impact on the performance of the KGCN model was investigated by varying the size of the sampling neighborhood, k , and the results are shown in Table 3. The model achieves the best performance when $k = 6$. A small k value cannot effectively aggregate neighborhood information, whereas a high k value can introduce noise and degrade the model’s performance.

The impact of the h -value on the model performance was also investigated and revealed that the best performance was achieved for $h = 1$, as shown in Table 4. Large h values lead to over-computation and amplify the noise in the model. The effect of embedding dimension on performance was investigated, and the optimal result was observed when $d = 16$, as illustrated in Table 5. A small d is not informative, while a large d results in overfitting, which ultimately lowers performance.

Table 4 Impact of the depth of receptive field

H	1	2	3	4
AUC	0.970	0.965	0.960	0.945
F1	0.903	0.891	0.888	0.856

Table 5 Impact of the dimension of embeddings

d	4	8	16	32
AUC	0.9399	0.9694	0.9694	0.8653
F1	0.8543	0.9010	0.9010	0.8392

6 Conclusion

In this paper, knowledge is introduced into the SPMW to solve the resource recommendation problem. The knowledge graph of workshop MR is constructed, and a knowledge-driven workshop MR recommendation method is also proposed. In the future, the knowledge graph for the SPMW requires improvement, and a recommendation algorithm that considers association relationships needs further in-depth study.

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Digital Twin-driven Dynamic Scheduling Cloud Platform for Disassembly Workshop



Jie Jiao, Gang Yuan, Xiaojun Liu, Guangdong Tian, and Duc Truong Pham

Abstract As an emerging technology that integrates multi-physics, multi-scale and multi-discipline properties, digital twinning can enable the interaction between the physical and information worlds. Disassembly has been widely used as an important method for manufacturing and green manufacturing. However, the uncertainty of the disassembly shop and the isolation of the disassembly information seriously affect the effective operation of the disassembly shop. In this paper, we propose a disassembly scheduling cloud platform based on digital twinning techniques. Compared with intelligent algorithms, it can effectively address the uncertainty factor in the disassembly shop. First, we build a workflow model graph for the disassembly scheduling cloud platform. Second, the whole process monitoring system of the disassembly scheduling workshop is constructed to monitor the disassembly dynamics in real time. Third, we build a digital twinning-based dynamic perturbation architecture for the disassembly scheduling cloud platform and use big data analysis techniques to predict and diagnose dynamic perturbations from multiple sources. Finally, the effectiveness of the proposed framework is validated by enterprise instances, on which the disassembly scheduling cloud platform is applied.

Keywords Digital twinning · Remanufacturing · Disassembly · Scheduling · Cloud platform

J. Jiao

School of Humanities and Social Sciences, Nanjing Forestry University, Nanjing 210037, China

G. Yuan (✉) · X. Liu

School of Mechanical Engineering, Southeast University, Nanjing 212000, China

e-mail: yuangang1224@163.com

G. Tian

School of Machinery and Vehicles, Beijing University of Civil Engineering and Architecture, Beijing 100044, China

D. T. Pham

Department of Mechanical Engineering, University of Birmingham, Birmingham COB152TT, UK

1 Introduction

Manufacturing has entered the digital age in the context of digitalization, information technology, manufacturing technology and network technology. With the integration and application of a new generation of information technology and manufacturing, advanced manufacturing strategies have been launched, such as industrial internet, industry 4.0 and China manufacturing 2025 [1–3]. Manufacturing is shifting from knowledge-based smart manufacturing to data-driven smart manufacturing. Realizing the interconnection and intelligent operation of the physical and infrastructural worlds can enable intelligent manufacturing in the information age. Dismantling as a new production activity provides the raw material for a smooth remanufacturing of the production schedule. Efficient dismantling not only saves natural resources and energy, but also effectively reduces environmental pollution. It is also an important guarantee for promoting the healthy development of circular economy and achieving sustainable industrial development [4]. Disassembly is one of the major technologies for remanufacturing, and its integration with digital twinning technology will make the production of disassembly workshops more standardized and intelligent. Dynamic scheduling problems for disassembly workshops will be a research hot spot for remanufacturing. Due to the different types of products in the disassembly workshop, there are complexities in the scheduling of production factors [5]. Multi-source dynamic perturbation factors in the disassembly shop reduce robustness. Dismantling workshops have long disassembly times, low disassembly rates and unreasonable resource allocation, which limit green sustainability. Traditional disassembly scheduling problems rely on intelligent algorithms for program optimization. With the advent of the big data era, intelligent algorithms have failed to keep up with the times in solving complex store scheduling problems. How to realize the interaction and integration between the physical world of manufacturing and the information world is the problem faced by smart workshop scheduling. Digital twinning uses digital methods to create physical entities in the real world and adds new capabilities to physical entities through virtual and real-world interaction feedback, data fusion analysis, and iterative optimization of decisions. Digital twinning is an intelligent technology that takes full advantage of multi-modal, big data and interdisciplinary smart technologies, among others, to provide real-time, efficient and intelligent services throughout the life cycle and act as a bridge between the physical world and the information world. The perfect combination of digital twinning and scheduling has enabled the disassembly workshop to move towards intelligent diversification. This paper provides a cloud platform framework for disassembly scheduling based on digital twinning techniques.

The remainder of our work is organized as follows. Section 2 reviews the relevant literature on digitizer twinning and disassembly scheduling. The framework of the disassembly scheduling cloud platform is shown in Sect. 3. Section 4 applies the proposed framework to case analysis. Finally, conclusions are drawn and prospects for future studies are provided in Sect. 5.

2 Literature Review

2.1 Digital Twinning

Digital twinning is an intelligent technique that uses a constructed digital virtual model to map a physical model to work in a real-world environment [6–8]. Data interaction, information fusion, iterative optimization, etc. can be performed between the two models [9, 10]. The main applications of digital twinning are product prediction, maintenance and service [11]. During the continuous improvement and development of digital twinning, the academic community has conducted related research on digital twinning modeling, information physics fusion, interaction and collaboration, and service applications. Tuegel et al. used virtual simulation data and physical model data to predict aircraft fatigue life [12]. Zhu et al. proposed a method of logistics resource allocation based on dynamic spatio-temporal knowledge graph, established a spatio-temporal consistent digital twin model, and conducted relational reasoning based on production line task information [13]. The workshop is the basis for the execution of manufacturing activities. To implement the concept of intelligent manufacturing and intelligent production, Tao et al explored the concept of digital twin workshop and designed the operation mechanism of DTS [14]. Schleich et al. suggested thinking about digital twinning through all stages of product realization and introduction a comprehensive reference model over the product life cycle to shape the digital twinning for design and production engineering [15]. Lv et al. designed a fault recognition and truncation algorithm based on active learning deep neural network and domain adversarial neural network to realize the application of digital twin technology in intelligent manufacturing [16]. Zhang et al. proposed a rapid customization design method based on digital twinning personalized production line, which synchronizes the digital model with the physical equipment to form a digital twin system [17]. Zhuang et al. analyzed the background of digital twinning and elaborated the connotation of product digital twinning [18]. Bomarito et al. proposed combining digital twinning with sensory particle technology to realize the detection, repair and replacement of real-time aerospace vehicles [19]. Qi et al. used the digital twinning idea to expand the online control concept under the IoT manufacturing and proposed a multi-system linkage optimization control method [20]. Dalla et al. constructed a digital twin model for monitoring production line power consumption to detect the digital monitoring between real-time data and digital twin data [21]. Sakdirat et al. build a production process model of the manufacturing system based on digital twinning technology to realize the transformation of digital enterprise [22]. Tao et al. proposed a digital twin-driven framework to utilize physical product data, virtual product data, and connected data that tie together physical and virtual products for product design, manufacturing, and service [23].

2.2 *Disassembly Scheduling*

In recent decades, the problem of disassembly scheduling has become one of the hotspots of remanufacturing research [24, 25]. Both domestic and international scholars have mainly used intelligent algorithms to study the problem of disassembly scheduling [26–28]. With the goal of minimizing the completion time, Imen et al. designed an improved genetic algorithm for solving dynamic shop scheduling problems [29]. Franz et al. used a systematic approach to optimizing the combination of disassembly sequences and shop scheduling [30]. Based on the interference relations between the components in the WEE-based 3D model, it is proposed a method to evaluate and decide on a selective disassembly sequence. With the minimum time as the optimization goal, Wang et al. designed a two-stage genetic algorithm to solve the problem of shop scheduling with uncertain processing time in flexible workshop [31]. From the perspective of operational scheduling, Cheng et al. proposed a new recycling management disassembly process model [33]. A heuristic method based on integer programming solves the problem of disassembly scheduling with multiple resources and multiple constraints [34]. Ehm presented a process data model for integrated disassembly sequencing and machine scheduling [35]. Liu et al. studied various algorithms and schedulers in virtual machine scheduling [36]. The functions of these schedulers are expressed by examining and classifying the various VM schedulers. Asta et al. designed a hybrid algorithm to solve multi-mode resources and prioritized restricted project scheduling problems [37]. Han et al. established a multi-objective migration bird optimization algorithm to solve the problem of multi-objective scheduling [38]. Aiming at the self-organizing configuration and adaptive collaborative control requirements of smart factory manufacturing resources, Zhang et al. proposed an intelligent modeling method based on CPS for real-time perception and self-determination of underlying manufacturing resource processing service status [39].

2.3 *Related Works*

Due to various uncertainties in the disassembly scheduling workshop, the integration of disassembly and digital twinning is key to solve the problem. As an emerging smart technology, digital twinning has been introduced into the disassembly shop to solve the complex problem of disassembly scheduling. The integration of production factors in the digital twinning technology enables collaborative optimization of the disassembly shop. Classified big data analysis in digital twinning plays an essential role in multi-source interference intelligent prediction and diagnosis. Cloud computing smart algorithmic systems in digital twinning techniques can be used for scheduling model optimization. Monitoring and control throughout the life cycle in digital twinning technology enables real-time data sharing of production factors in disassembly. The virtual shop interacts with real-time information from

the physical shop, and can be driven by process routes in the disassembly shop. The fully-featured, fully-processed, fully-smart integrated digitizer technology solves the existing problems of the disassembly shop.

3 The Framework for Digital Twin-Driven Disassembly Scheduling Cloud Platform

3.1 Disassembly Scheduling Cloud Platform

In this paper, we introduce a scheduling cloud platform for disassembly workshops based on digital twinning techniques. Existing disassembly workshop models, algorithms and big data are transferred to the scheduling cloud platform terminal using smart technologies such as IoT and cloud computing. The digital twins-driven disassembly scheduling cloud platform requires the following conditions: (1) The digital twinning workshop includes the establishment of a “model-constrain-disassembly” multi-objective model, intelligent management of the disassembly workshop, optimization of the disassembly process, and real-time interaction between the physical workshop and the virtual workshop. (2) The digital twinning technology integration of “physical workshop-virtual workshop-cloud platform” includes multi-source and multi-type data collection and storage, sensor layout optimization and data collaborative uploading, and three-way mapping between virtual reality workshop and cloud platform. (3) Digital intelligent service technology, including multi-class heterogeneous data fusion, multi-element collaborative production analysis, multi-source perturbation data prediction, disassembly energy consumption, time, and environmental optimization. The above functional guarantees provided by digital twinning can enable the scheduling cloud platform to operate properly and thus enable multi-objective, multi-constrained and multi-type intelligent scheduling.

The disassembly scheduling cloud platform starts from disassembly requirements and performs disassembly resource retrieval and preliminary evaluation of disassembly performance. Then, the dynamic scheduling adjustment is performed on the initial disassembly scheme and the final disassembly task is completed. The framework of the disassembled scheduling cloud platform is illustrated in Fig. 1. Disassembly process, usage status, service life and manufacturing disassembly information of different types of products are uploaded to the scheduling cloud platform to generate a disassembly database. We integrate technologies such as disassembly optimization models, intelligent algorithms, big data, cloud computing, and intelligent decision-making methods to upload disassembly scheduling data to cloud platforms. For the generation of the disassembly scheme, there are two scheduling flow routes in the cloud platform. Path 1 is shown by the yellow line, that is, “scheduling cloud platform-virtual workshop-physical workshop”. Depending on the specific disassembly conditions and disassembly requirements, we establish virtual disassembly scheduling by matching and retrieving in the resource bank of the cloud platform. The

virtual workshop optimizes the disassembly scheduling scheme. When the scheme meets the disassembly requirements, a disassembly instruction is issued to the physical workshop, which provides real-time information feedback to the cloud platform and the virtual workshop. If the solution needs to be adjusted, the cloud platform loops the above operations; Otherwise, the task of product removal is completed. The green line is shown as path 2, that is, “virtual workshop - disassembly requirements - cloud platform - physical workshop”. When the requested information is not retrieved in the scheduling cloud database, a virtual disassembly is performed, after which the initial solution is fed back to the decision maker. The decision maker reconstructs the optimization model based on the market demand and the company’s disassembly criteria. Loop iteration until the optimal disassembly scheme is obtained. Finally, the disassembly instructions are sent to the physical store and the new disassembly schedule data is stored on the cloud platform.

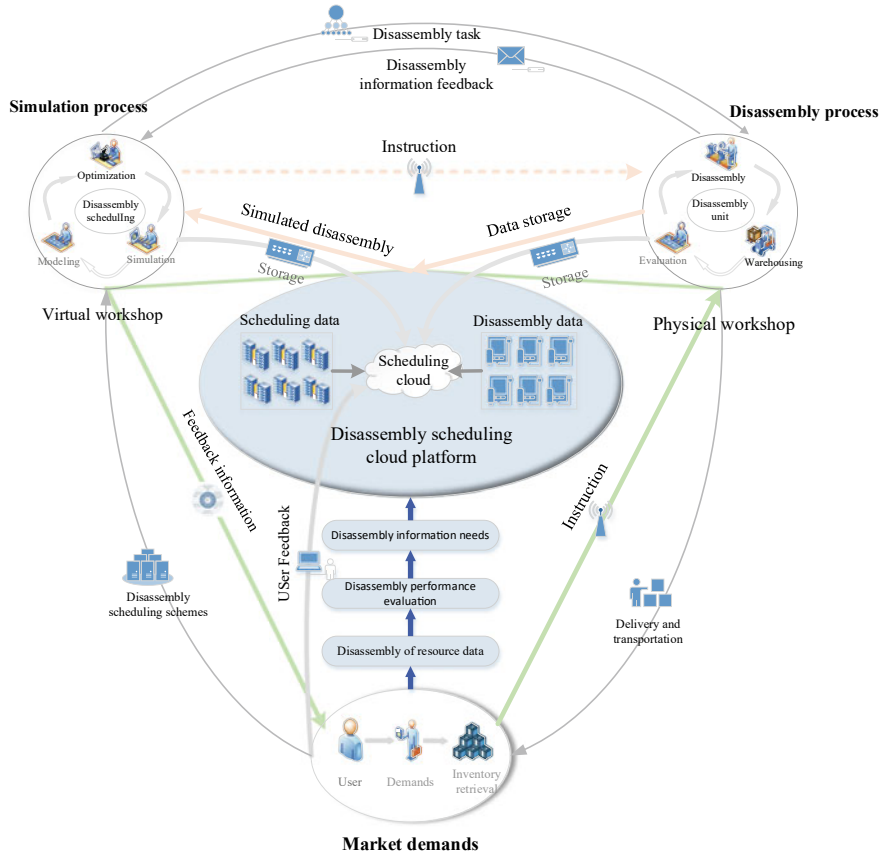


Fig. 1 The framework of disassembly scheduling cloud platform based on digital twinning

3.2 Disassembly Scheduling Workshop Whole Process Monitoring System

The disassembly workshop is divided into six main parts: disassembly, equipment, staff, environment, remanufacturing and recycling. Production elements of the physical store use sensors to interact with information from the virtual shop. The physical store transmits real-time data to the virtual store. The virtual shop delivers real-time feedback and control commands to the physical store. The recycling part of obsolete products includes the acquisition, transportation, warehousing, policy subsidies, etc. The disassembly part includes the manufacturer, type, weight, specification, disassembled person, disassembly time, delivery date, disassembled product identification code, etc. The equipment part includes mechanical energy consumption, losses, maintenance, repair, operation status, etc. The environmental section includes equipment temperature, pressure, noise, dust, three waste emissions, etc. The employee part includes the skills and knowledge of the employee, working hours, position status, task progress, etc. The manufacturing part includes reusing key components, craftsmanship, special needs in the secondary market, etc. The interaction information between physical and virtual workshops will be uploaded to the scheduling cloud platform for iteration and interaction. The scheduling cloud platform monitors the production factors in real-time based on the analyzed information, such as storage time, transportation time, transportation path, equipment opening and closing time, idling time of disassembled parts, etc. All data in the disassembly process will utilize three-dimensional mapping technology of digital twinning (virtual and real workshop-cloud platform-physical workshop). The scheduling cloud platform is stored for full cycle monitoring in recycling, pre-processing, performance testing, disassembly, crushing, color classification, storage and marketing. Data is uploaded collaboratively based on digital twinning, and the data analysis and monitoring system is used to implement the entire process monitoring system of the scheduling cloud platform. Figure 2 shows the overall process monitoring of the disassembly scheduling cloud platform.

3.3 Disassembly Scheduling Cloud platform Dynamic Disturbance Architecture

Due to the uncertainty, there are numerous uncontrollable perturbations in the disassembly shop, such as disassembly characteristics, cloud characteristics, etc. At the same time, there are different disassembly requirements in the disassembly shop. When the disassembly shop is disturbed, it causes the quality of the scheduled work to deteriorate and affects the efficiency of the shop. Therefore, simulations and predictions of workshop disturbances are extremely valuable. We use big data analysis techniques to analyze data stored in a cloud platform to predict possible

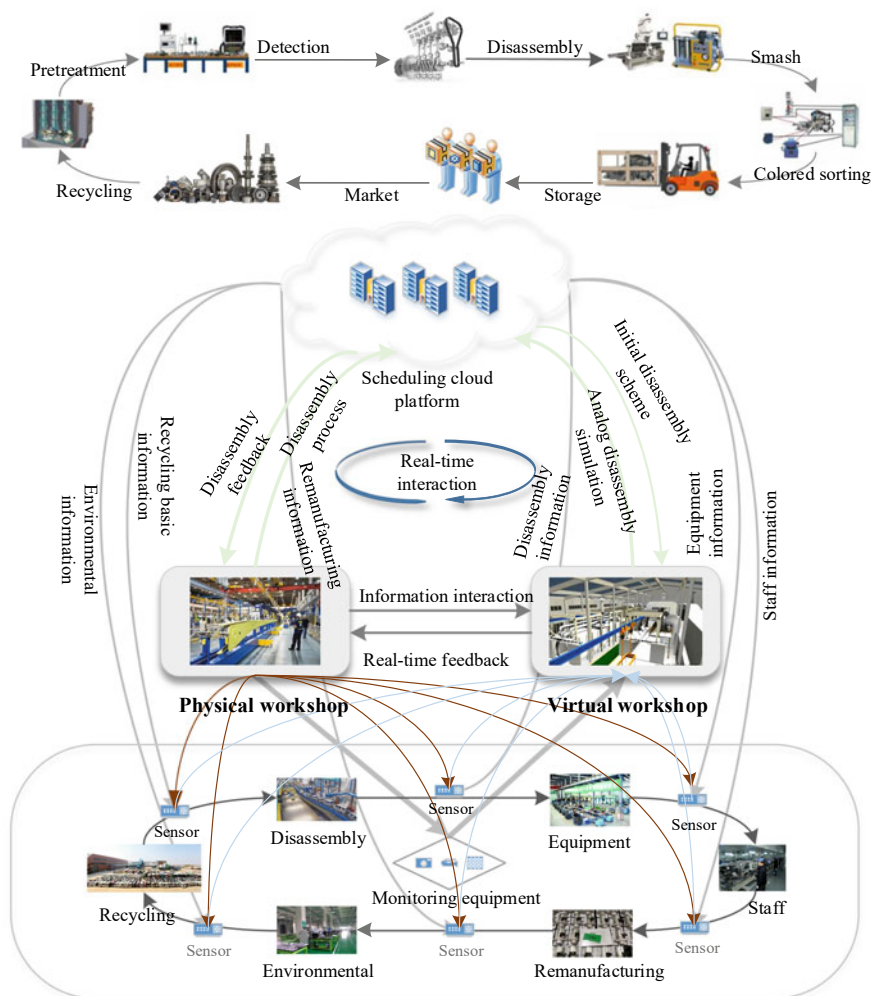


Fig. 2 The whole process monitoring of the disassembly scheduling cloud platform

disturbances. The system will develop a new solution to address the possible perturbations in the above prediction. The real-time data interaction between simulation prediction and decision evaluation enables dynamic optimization. Specifically, the cloud platform will discover perturbation factors and analyze data features based on digital twinning. The cloud platform will also determine the impact of dynamic interference on current scheduling schemes. When the influence degree of the perturbation scheduling scheme exceeds the defined influence value, dynamic perturbation decision evaluation is required.

In the decision evaluation part, the scheme search is first performed on the cloud platform. If the corresponding disassembly scheme can be searched, the decision

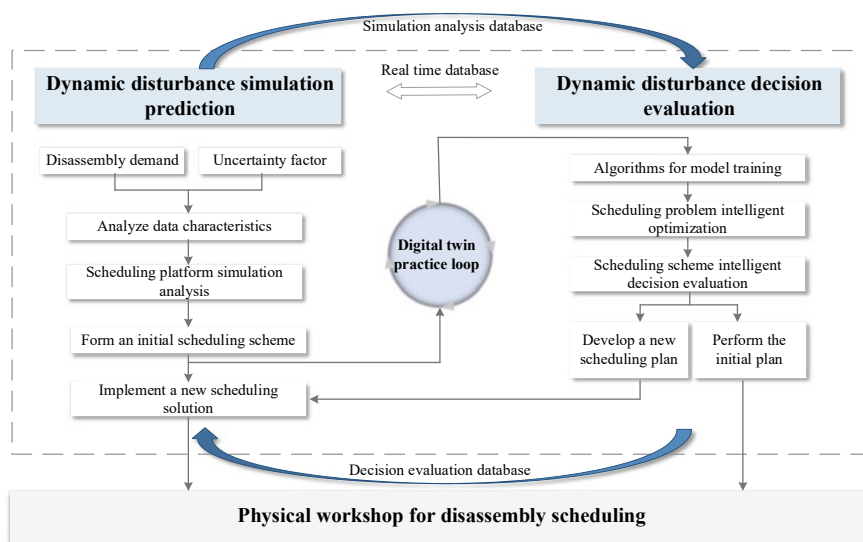


Fig. 3 Digital twin-based architecture of disassembly scheduling cloud platform dynamic disturbance

evaluation performs the initial disassembly scheme. If a matching disassembly scheme cannot be searched, the virtual workshop optimizes the model using an intelligent algorithm. Then, a new scheme is developed through intelligence-based decision evaluation and applied to physical workshops. Fig. 3 shows the digital twin-based architecture of the disassembly scheduling cloud platform for dynamic disambiguation.

3.4 Scheduling Process of the Disassembly Scheduling Cloud Platform

Different from traditional scheduling methods, disassembly scheduling based on digital twinning technique is an intelligent scheduling method. The cloud platform can automatically decide to select or optimize the disassembly scheme based on specific conditions. In an ordinary disassembly workshop, the disassembled parts are disassembled according to the disassembly procedure and distributed to the corresponding workstation for disassembly. However, each station will be subject to various levels of constraints and management during the disassembly process, and the resources available for deployment are limited. The non-sharing of resources greatly affects the manner and efficiency of disassembly.

Cloud scheduling in digital twinning environments is a networked configuration. Its strong internal correlations can break through geographical limitations and

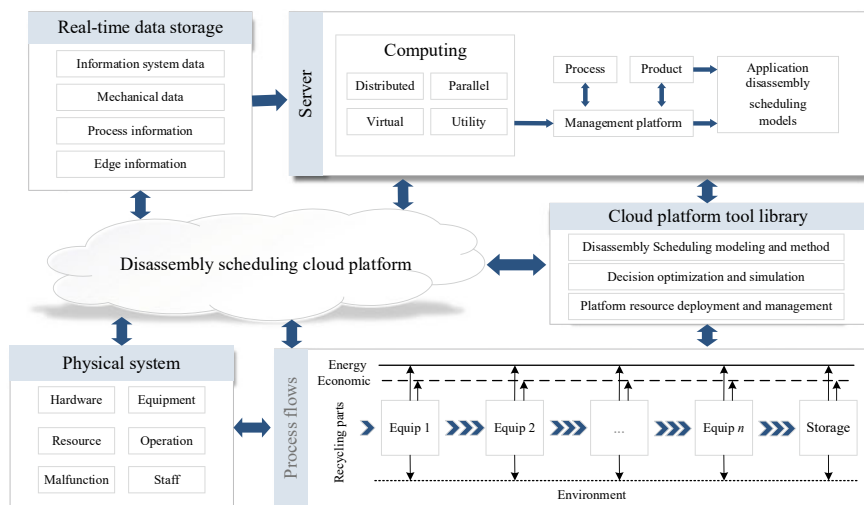


Fig. 4 Scheduling process of the disassembly scheduling cloud platform

administrative restrictions. Decomposition is no longer hierarchical decomposition control but intelligent optimization. An optimal scheme can be formulated by rationally coordinating the resource information usage of the disassemblers. In addition, smart scheduling for cloud platforms uses smart technologies such as IoT, cloud computing, big data, and digital twinning. The cloud platform can monitor and transmit real-time data throughout the disassembly process. Therefore, cloud-based production scheduling methods are more intelligent and can consider the combined influences of economy, energy consumption and environment, and are more suitable for multi-dynamic, multi-variate production environments. Figure 4 shows the scheduling process of the disassembled scheduling cloud platform.

4 Case Analysis

4.1 Model Establishment

In the case of an enterprise disassembly shop, the frame diagram of the disassembly shop is constructed with reference to the production elements of the physical shop. When using digital twinning techniques, three aspects of the model, constraints and actions need to be considered. The digital twinning model for the disassembly scheduling workshop consists of a production factor model and an association model. Therefore, it is necessary to build a material library model, a mechanical device

model, an environment model, a decision evaluation model, a multi-objective optimization model, and a human-machine-object interaction model. In order to interconnect the established models, it is necessary to build association models: sensor models, disassembly models, product information models, etc. Constraints for disassembly scheduling include disassembly constraints, work-time constraints, economic constraints, energy constraints, priority constraints, environmental constraints, etc. This ensures that the working mechanism of the digital twin in the workshop can realistically mimic the working state of the physical workshop. At the same time, it is necessary to coordinate the operation of equipment, personnel deployment, component transfer, environmental adjustment, and real-time formation transmission. By analyzing the above three aspects, the information of physical and virtual workshops can be interactive and integrated in real time. Finally, the physical workshop and the virtual work shop are connected to the factory cloud platform. The cloud platform deploys in-formation resources, disassembly monitoring, multi-source dynamic perturbation, and decision optimization.

4.2 *The Model Operating Mechanism*

The operation process of the digital twin-driven scheduling model is shown in Fig. 5. The preset disassembly scheme is simulated disassembly in a virtual workshop of the cloud. If the simulation results are not too different from the expected values, the cloud platform generates a work path and a schedule of disassembly sequences. The work path and disassembly process are then output to the physical store. The workbench performs the disassembly task according to the established route. Depending on the work experience and the disassembly process, disassembled parts and equipment can be matched with real-time data transmission and connectivity tasks, thereby improving the work efficiency of the workshop. During the work process, the disassembly information is integrated with the cloud platform. Cloud platforms perform big data prediction based on feedback from historical data. If there is interference, the disassembly process parameters are adjusted, if not, the machining data is saved.

The application of this case is reflected in five main aspects. (1) Network-physical health level. Data interconnections between virtual and physical workshops enable monitoring of the entire disassembly process. (2) The disassembly execution level. The disassembly parameters are modeled and simulated to analyze whether there is interference between the disassembly processes. The special case of a virtual workshop is simulated, and the simulation results are fed back through the simulation data channel. (3) System network integration level. The internal coordination between the various systems can be reasonably adjusted to disassemble equipment, mechanical equipment, transportation equipment, etc. (4) Dynamic disturbance level. The multi-source dynamical perturbations of the scheduling process are mainly classified into disassembly uncertainty and cloud feature uncertainty. Sensors are embedded in production equipment to detect various data, and scheduling cloud platform big data analytics technologies to predict and diagnose faults. Depending on the level

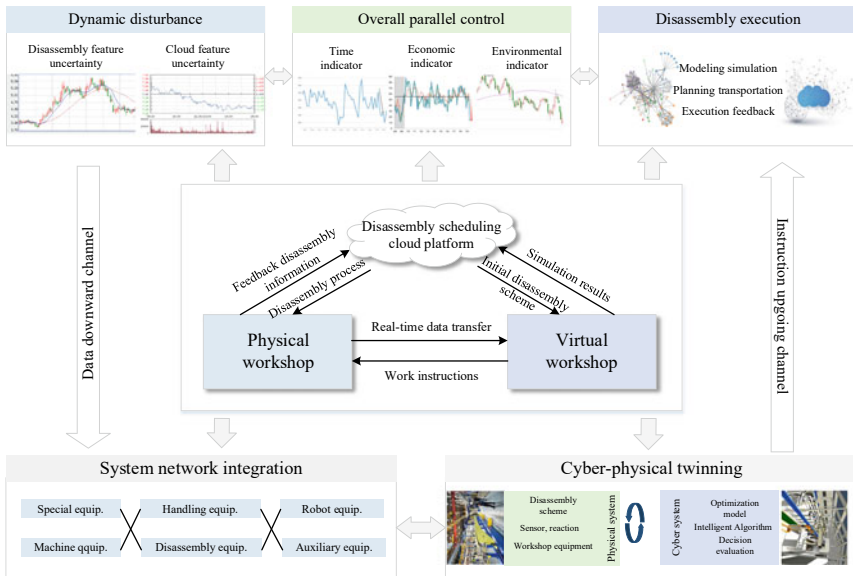


Fig. 5 Operational architecture diagram of disassembly scheduling cloud platform based on digital twinning

of impact, whether to perform the rescheduling is determined. If it is executed, the virtual workshop makes process changes for the perturbed situation, and through a series of simulation, evaluation, validation and optimization cycles, a new production scheduling process plan is formulated. (5) The overall parallel control level. Time, economic and environmental metrics are important factors in the scheduling process of a disassembly workshop, and multi-objective algorithms are used for iterative optimization. The control system performs multidimensional and hierarchical cluster analysis by collecting real-time monitoring data. The store scheduling process is adjusted through performance indicator curves, trends, and features.

5 Conclusion

With the deep implementation of China's manufacturing power strategy, a new generation of information technology and artificial intelligence are deeply integrated with the manufacturing industry. Digital twinning enables the interplay between physical and virtual workshops and is central to the concept of intelligent manufacturing. Nowadays, disassembly workshops are moving in the direction of intelligence. The effective operation of scheduling is severely affected by the uncertainty of disassembly, which limits the intelligent development of manufacturing and service manufacturing. In this paper, we combine digital twinning to propose a theoretical

framework for disassembly scheduling cloud platforms and provide theoretical guidance for in-situ disassembly. The main work of this paper is as follows: First, we propose a disassembly scheduling cloud platform framework based on digital twinning. Second, construct a disassembled full monitor for scheduling. Third, in order to solve the dynamic perturbation problem in the disassemble workshop, the integration of digital twinning and big data provides dynamic perturbation prediction and perturbation policy formulation for scheduling. Finally, the proposed digital twinning model is validated with disassortative examples. This paper attempts to explore the application of digital twinning techniques in a disassembly workshop. Future research directions can optimize the IoT network for physical store disassembly elements and build big data-driven data analysis and prediction models.

Declarations Availability of data and materials The data and materials presented in this article are available.

Authors' Contributions Jie Jiao was in charge of the whole trial. All authors read and approved the final manuscript.

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IoT-Driven Digital Twin for Improved Product Disassembly in Remanufacturing



Celia Garrido-Hidalgo, Luis Roda-Sanchez, F. Javier Ramírez,
and Teresa Olivares

Abstract Remanufacturing, aimed at restoring end-of-life products to like-new condition, has become an essential value-recovery strategy to guarantee sustainable industrial development. Despite its innumerable social, economic and environmental associated benefits, the high uncertainty on the condition of end-of-life products represents a major barrier to the automation of disassembly tasks. Therefore, the effective adoption of remanufacturing in industries is limited these days. In this context, worldwide consolidation of the Internet of Things has led to the recent creation of massive data ecosystems, the potential of which is yet to be exploited in a remanufacturing domain. Data analytics and predictive planning built on top of the Digital Twin concept can significantly improve decision-making through the modelling of “what-if” scenarios leveraging real-time information collected and made available by Internet of Things network infrastructures. However, the remote monitoring of end-of-life products and the integration of information from multiple sources are not trivial tasks, which respectively deal with large-scale wireless network deployments and heterogeneous spatio-temporal patterns. To shed light on this matter, this work explores one of the recent advances of Digital Twin infrastructures towards remanufacturing, as well as open challenges and research directions in the field of data-driven decision-making. Second, relevant sources of information are discussed and reviewed, which are then classified into three hierarchical categories: (i) product-condition information, (ii) context information, and (iii) spatio-temporal features. Finally, a conceptual Digital Twin model leveraging multi-source information integration is proposed, which motivates a case study for data-driven decision-making in

C. Garrido-Hidalgo (✉) · T. Olivares

Departamento de Sistemas Informáticos, Escuela Superior de Ingeniería Informática de Albacete,
Universidad de Castilla-La Mancha, Albacete, Spain

e-mail: Celia.Garrido@uclm.es

C. Garrido-Hidalgo · L. Roda-Sanchez · T. Olivares

Instituto de Investigación en Informática de Albacete, Albacete, Spain

L. Roda-Sanchez

NEC Ibérica, Albacete, Spain

F. Javier Ramírez

Departamento de Administración de Empresas, Escuela Técnica Superior de Ingenieros
Industriales de Albacete, Universidad de Castilla-La Mancha, Albacete, Spain

end-of-life product recovery considering context information. This work represents a step further in the adoption of the Internet of Things in the remanufacturing domain by addressing both data collection and exploitation dimensions towards Digital Twin modelling.

Keywords Remanufacturing · End-of-Life · Internet of Things · Digital twin

1 Introduction

Aimed at providing daily-life objects with low-cost sensors and wireless communication interfaces so that they can sense and interact with their environment, the impact of the Internet of Things (IoT) has been significantly influenced by the latest developments in the field of Artificial Intelligence (AI).

On the one hand, the exponential growth of IoT connectivity networks and solution providers has impulsed the formalization of massive Machine-Type Communication (mMTC) as one of the three Beyond 5G (B5G) core service areas of research to guarantee large-scale interoperability in the coming years [1]. Regulated congestion control and collision avoidance techniques are among the most relevant resource-allocation strategies in the IoT domain to guarantee reliability in large-scale network deployments [2].

On the other, IoT has already become an essential aspect of many business architectures as a means to transparently collect vast amounts of data [3]. Specifically, open sources of information such as publicly available datasets (e.g., Fraunhofer Big Data AI [4]) or governmental databases play a vital role in the growth and development of AI-powered systems. Among these, the Digital Twin (DT) concept—a virtual mirror representation and modelling of physical entities and their linked properties [5, 6]—is becoming increasingly feasible through advanced data analytics and lightweight Machine Learning (ML) models trained on top of such massive data generated by embedded IoT devices.

While the implementation of DTs is already significant in the domains of design, production, manufacturing and maintenance, their adoption to support remanufacturing remains unveiled. Despite potential benefits being expected in terms of resource optimization, enormous challenges need to be first overcome. These include high uncertainties on the end-of-life (EoL) condition of products, the lack of a ubiquitous connectivity infrastructure able to monitor products across spread locations, or limited access to linked information caused by data privacy policies, among others [7].

This work explores the adoption of IoT and DT in different remanufacturing perspectives, which motivates the proposal of a conceptual DT model leveraging IoT communication infrastructures for remanufacturing, and the exploration of different data processing possibilities for data-driven decision-making. To do so, a collection of relevant publicly-available data sources to be exploited in different remanufacturing scenarios is presented, which are then used to explore the potential of the proposed DT in specific remanufacturing and IoT network management use cases.

2 Background

This section explores the state of the art, recent advances and major barriers to IoT and DT adoption in different remanufacturing domains. First, Sect. 2.1 provides a scoping review of relevant IoT approaches to reverse supply chain management, waste management, and product disassembly. Second, Sect. 2.2 addresses the DT concept in further detail addressing different AI-oriented approaches of interest towards its industry adoption.

2.1 IoT-Driven Remanufacturing

There exist numerous IoT-enabled approaches to manufacturing in the literature under the well-known Industry 4.0 development paradigm [8]. While high potential is expected from IoT technologies as well in the remanufacturing domain towards minimising EoL product-condition uncertainties through lifecycle monitoring, limited contributions exist to date in the literature. Specifically, those in the domains of (i) *reverse supply chain*, (ii) *waste management*, and (iii) *product disassembly* are reviewed in the following lines.

In the first, the information-oriented requirements across reverse supply chains were first reviewed in [9] through a case study on the recovery of EoL lithium-ion electric vehicle batteries (EVBs), with a heterogeneous IoT communication network deployment being proposed to guarantee information integrity throughout different recovery stages of EoL products. Similarly, authors in Parry et al. [10] investigated *orderless inventory replenishment* through the use of IoT to capture consumer-use information of products towards improved visibility when reaching their EoL stage.

The benefits of IoT adoption for product and component recovery at the EoL stage of waste electric and electronic equipment (WEEE) management was addressed in [11]. In terms of hybrid approaches, the integration of big data and IoT technologies was studied in Gu et al. [12] within a WEEE recovery use case, while the authors in Hrouga et al. [13] addressed asbestos waste management through the combined use of IoT technology and blockchain to guarantee information integrity.

In the third, the majority of existing contributions rely on Radio Frequency Identification (RFID) technology for the collection and transmission of products' lifecycle information to support information availability upon disassembly, with two representative works being [14, 15]. With the focus put on human-robot collaboration to support product disassembly, there exist representative works that contributed from an IoT-oriented perspective to disassembly through wireless communication network dimensioning and design [9, 16], sensor embeddedness [17, 18], or real-time data processing from wearable nodes [19].

2.2 DT Fundamentals

The *Digital Twin* concept was first coined in the product lifecycle management domain as a means to embedding the information of a specific physical system across its different lifecycle stages [20]. Ever since, its formal definition has gone through enormous transformation, which is partially attributed to the emergence and rise of key-enabling technologies such as IoT, virtualization, or AI-driven analytics [21]. Nowadays, the DT is not only conceived as a virtual representation of a physical entity and its linked properties, but also as the set of data-driven models used for the prediction and planning of its behavior [22, 23].

Van Der Horn and Mahadevan [24] identified three primary components of a DT, the implications of which are discussed in the following lines in the remanufacturing domain:

- *Physical reality*. This component refers to a physical entity and its surrounding environment. Recent advances in the field of sensor-embedded products have made possible fine-grain collection of real-time data to be used for lifecycle condition monitoring. In these regards, Lim et al. [25] identified static environmental data and real-time sensor updates as two key sources towards EoL product condition monitoring and predictive maintenance.
- *Virtual representation*. The DT's virtual representation refers to a set of data and/or computational models that accurately describe the physical reality with a certain abstraction level. In this sense, Ploennigs et al. [3] identified *Simple Twins*, *Advanced Twins*, and *Fully Mature Twins* as three major abstraction levels supporting, respectively: data integration and analytics, timeseries prediction and optimization, and online learning and own decision-making. Knowledge-graph technology describing entities and their relationships as a set of triples (*subject*, *predicate*, *object*) are highly beneficial for developing remanufacturing DTs given the hierarchical nature of products and their disassembled parts [26].
- *Information-exchange*. Data-intensive applications within the DT concept are governed by IoT communication infrastructures, which need to guarantee real-time information collection, processing and reliable transmission. In this context, mMTC environments need to be explored in order to alleviate scalability concerns in wireless communication networks through tight integration of edge computing within end nodes and resource-optimization techniques for collision avoidance [27].

2.3 Research Gap

This work fills a gap in terms of data-driven decision-making towards IoT-enabled remanufacturing through the design of a conceptual model built on top *physical twin*, the *virtual twin*, and *information exchange* dimensions. To the best of our knowledge,

there are no other works in the literature that: (i) address data ingestion and network planning of DT-enabled condition monitoring and remanufacturing from a theoretical perspective, and (ii) propose EVB-oriented use cases to exploit open sources of data from a practical perspective.

3 IoT-Enabled DT for EVB Remanufacturing

This section addresses a DT model design on top of IoT-embedded products supporting condition monitoring for remanufacturing. The main data-driven components of the DT are detailed in Sect. 3.1 in addition to remanufacturing-oriented use cases relying on enriched data analytics and semantic modelling. Section 3.2 provides a collection of openly-available data sources to be exploited in the remanufacturing domain. Finally, Sect. 3.3 addresses a use case for the recovery of EoL EVBs on top of a set of DT components from the presented model design and studied data sources.

3.1 Conceptual Model Design

Figure 1 presents a DT model proposal built on top of open data sources providing relevant *context* and *spatio-temporal* information relevant for EoL product condition monitoring, as well as local *product lifecycle sensor data*. These are extended in Sect. 3.2.

The three major DT components included in Fig. 1 are: (i) a *data ingestion pipeline* responsible for open source data collection, formatting and analysis within a common data model, (ii) a *wireless communication network* responsible for IoT-oriented product condition information transmission, and (iii) different *data analytics engines* deployed at both product-level and DT level for, respectively, product-oriented predictions and global predictions fed by different “what-if” scenarios and remanufacturing use cases.

Product-level DTs represent different entities within the overall DT model, which are designed with a view to minimising bandwidth usage within large-scale IoT network deployments. To do so, edge computing is proposed inside product-embedded microcontroller units (MCUs) for extracting, based on a set of pre-trained model predictions, relevant information to be transmitted to the global DT instead of large amounts of raw sensor data.

The overall DT model itself is composed of a set of unitary prediction modules (base models in Fig. 1), such as anomaly detection or component clustering, and a series of utility functions for spatio-temporal data analysis. Similarly, the data ingestion pipeline should include key modules for the automated collection, processing and augmentation of data sources being provided in different formats such as CSV, XLS, XML or RDF.

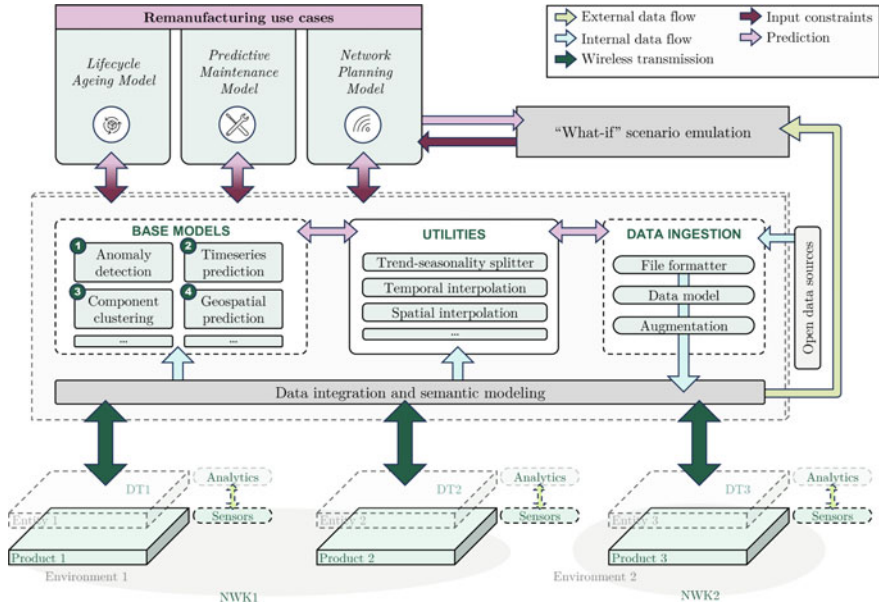


Fig. 1 DT model design for sensor-embedded product remanufacturing

Three vertical remanufacturing use cases are included in Fig. 1, which are fed with different application-oriented constraints (“what-if” scenarios) while being built on top of a specific set of base models, utility functions and data-ingestion pipelines within the overall DT. Prediction results obtained are, in turn, used to feed the system towards short- and long-term planning oriented to both EoL products and deployed IoT network infrastructures.

3.2 Relevant Data Sources for EoL EVB Remanufacturing

This section presents relevant openly-available data sources for the remanufacturing and associated operations of EoL EVBs, which are briefly described in the following lines and specified in Table 1.

- *Product-condition information.* This information is mainly composed of local life-cycle sensor data from IoT-enabled products in addition to available product specifications provided by original equipment manufacturers (OEM).
- *Context information.* Based on each product’s location, this information is obtained from a collection of openly-available data sources including weather conditions such as relative humidity (RH), temperature, or barometric pressure. Additional context information is included in Table 1.

Table 1 Sources of information

Year	Resource description	Access
2020	Universal battery performance and degradation for electric aircraft	[28]
2020	Battery and heating data in real BMW i3 driving cycles	[29]
2021	Collection of battery ageing datasets according to number of cells and chemistry	[30]
2022	Lithium-ion EVB aging diagnosis based on real-driving cycles	[31]
2022	Extraction of changes in battery properties from dynamic data	[32]
2022	Prediction of both remaining charge and remaining useful life	[33]
2022	Load profiles for electric vehicle charging in UK	[34]
2022	Context information for electric vehicle in USA	[35]
2022	Electric vehicle charge points in EU	[36]
2023	WEEE collection points in EU	[37]
2023	Circular economy in EU	[38]
2018	Integrating sustainability and remanufacturing aspects	[39]
2021	Infrastructure for charging electric vehicles in EU	[40]
2022	Electric-vehicle charging infrastructure in USA	[41]

- *Spatio-temporal features*. This source is mainly composed of information about available infrastructure for electric vehicles charging and sustainability and remanufacturing integration aspects.

3.3 Product- and Network-Oriented Use Cases

The *lifecycle ageing* and *predictive maintenance* remanufacturing-oriented use cases specified in Fig. 1 aim to leverage the DT model for predicting and/or improving a specific product's state-of-health (SoH), while the *network planning* one focuses on the reliability of wireless communications in large-scale DT network deployments through predictive planning.

This section addresses in more detail the data sources and DT components on top of which *lifecycle ageing* and *network planning* use cases are built in order to address both product- and a network- oriented perspectives of the proposed DT. To do so, the focus is put on the lifecycle, ageing and maintenance of EVBs as target product, whose remanufacturing is expected to raise special interest in the coming years.

3.3.1 Lifecycle Ageing of EVBs (Product-oriented Case)

Relevant datasets for training ML models in the ageing of EVBs are analysed in Table 1. Of these, the dataset by Pozzato et al. [31] is considered of special relevance, since it provides both raw and processed diagnosis data of different cells across up to 219 EVB's cycles (each consisting of 6 specified steps). Diagnosis tests carried out include reference performance tests (RPTs) on capacity, hybrid pulse power characterization (HPPC) and electromechanical impedance spectroscopy (EIS).

The raw measurements provided in this dataset can be potentially used for the training and fine-tuning of battery ageing models able to estimate the battery's SoH and the degradation of each of its cells under different driving profiles. While there is already plenty of literature covering this research domain, an additional constraint arises in IoT-enabled DTs, since data payloads to be transmitted from end products (EVBs) to the DT core need to be minimised as far as possible and, in turn, constrained IoT devices are not suitable for dealing with computationally-expensive models.

To these ends, we propose a data-processing and exploitation pipeline from the DT components highlighted in Fig. 1: a simplified replica of the core DT model from Fig. 1 built at entity level and fully trained with local data measurements. This approach leverages edge computing at entity level (that is, at every EVB being monitored), with data ingestion components being omitted due to local data measured by sensors being expected to share a common data model. High-level predictions could be used at entity level for the generation of ageing alarms to be transmitted to the core DT, including base models like *anomaly detection*, *component clustering*, or *feature importance* for regression. The possibility of deploying a generic pre-trained model with openly-available EVB's ageing data needs to be explored, following the Transfer Learning approach, which would significantly reduce end-node complexity at the expense of lower accuracy performance that could still satisfy application requirements.

3.3.2 Large-Scale Planning of Transmissions (Network-oriented Case)

Regarding the maintenance and resource-allocation planning of the IoT network infrastructure that guarantees information exchange, we propose the exploitation of data collected from every entity regarding transmission needs such as sending periodicity, payload length, or expected location to train a centralized ML model responsible for the allocation of resources on demand according to short- and long-term predictions. In this domain, an approach using the LoRaWAN technology for the transmission of EVB-related data was recently addressed in the literature as part of our previous work, which can be accessed in Garrido-Hidalgo et al. [16, 42].

In this direction, we propose to reduce as much as possible the computational load at IoT nodes by centralizing prediction modules inside the core DT model. Feasible components for these means are *data ingestion and integration* modules (as a means to semantically model relevant data sources influencing the overall network's performance), utilities such as *trend-seasonality splitting* (in order to identify device

desynchronization over time, for instance), or *timeseries prediction* modules, which guarantee large-scale reliability through scenario emulation.

4 Conclusions and Open Research Directions

This work explores recent insights on the adoption of IoT and DT in different remanufacturing perspectives, and proposes a conceptual DT model for the remanufacturing of EoL EVBs. This model is built on top of a *physical twin*, the *virtual twin*, and *information exchange* dimensions, which are regarded as three key DT components [24]. A collection of relevant publicly-available data sources to be exploited in different remanufacturing scenarios is provided as well, with *life ageing of EVBs* and *large-scale planning of transmissions* being respectively detailed as product-oriented and network-oriented use cases leveraging the proposed DT model.

This research gathered a series of preliminary insights towards IoT-enabled DT modelling in the remanufacturing domain. However, one of its the main limitations lies in the lack of experimental results regarding the proposed use cases, which could be overcome through the following set of open research directions:

- Study of the applicability of unsupervised learning techniques, such as k-means clustering or hierarchical clustering, for component ageing labelling in sensor-embedded products' lifecycle monitoring.
- Based on the previous, an AutoML approach could be addressed through an automatic feature engineering and selection pipeline in order to fit individual ML models for each timeseries cluster centroid identified through clustering.
- Alternatively, with a view to minimising computational load in resource-constrained IoT devices, a promising research direction lies in further data-source exploration for enrichment and augmentation in order to train a generic ML model to be reused and fine-tuned at every embedded IoT device.

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Knowledge-Driven Scheduling of Digital Twin-Based Flexible Ship Pipe Manufacturing Workshop



Hongmei Zhang, Sisi Tian, Ruifang Li, Wenjun Xu, and Yang Hu

Abstract Pipe manufacturing is an essential phase in ship construction. Aiming at the problems of insufficient dynamic response-ability, human-oriented workshop control, and unbalanced equipment load in ship pipe manufacturing workshops, a knowledge-driven scheduling method for flexible ship pipe manufacturing workshops is proposed to comprehensively improve the efficiency of ship pipe manufacturing. A digital twin-enabled scheduling framework for flexible ship pipe manufacturing workshops is designed. On this basis, an ontology model of ship pipe manufacturing is described by analyzing the data of the ship pipe manufacturing workshop. And according to the low-volume and multi-variety manufacturing demand, a knowledge-driven multi-objective optimal shop scheduling model is constructed based on the equipment selection rules and scheduling optimization rules produced by ontology knowledge inference. Then, an improved Multi-objective Evolutionary Algorithm Based on Decomposition (IMOEAD) is proposed. Finally, a case study in a pipe machining production line is studied to validate the proposed approach and the simulations show that the proposed approach is superior to other scheduling algorithms and decision makers can obtain more effective production execution plans.

Keywords Ship pipe manufacturing workshops · Knowledge-driven · Digital twin · Scheduling · IMOEAD

H. Zhang (✉) · S. Tian · R. Li · W. Xu

School of Information Engineering, Wuhan University of Technology, Wuhan 430070, China

e-mail: zhm18571656072@whut.edu.cn

Hubei Key Laboratory of Broadband Wireless Communication and Sensor Networks, Wuhan University of Technology, Wuhan 430070, China

Y. Hu

China Ship Development and Design Center, Wuhan 430064, China

1 Introduction

Ship pipe manufacturing is an essential part of ship manufacturing [1]. And due to the low-volume and multi-variety characteristics of ship pipes, the deployment of production resources in a ship pipe manufacturing workshop (SPMW) has great flexibility, and it is difficult to unify the mass production of pipes. That is to say, ship pipe manufacturing is a kind of flexible manufacturing, and the corresponding workshop can be called a flexible ship pipe manufacturing workshop (FSPMW).

However, traditional ship pipe production relies excessively on operators' experience and has significant limitations. In this way, knowledge is not effectively used, and the level of digitalization of pipe manufacturing is low. The lack of effective management and guidance of manufacturing process knowledge generated will not only lead to the waste of a large number of resources but also to problems such as low production efficiency and high error rates. Ontology is a formalized, clear, and detailed description of community knowledge sharing [2]. The knowledge-based approach to model construction facilitates the integration of multiple types of knowledge, improves the efficiency of knowledge utilization, and makes the model more interpretable. Thus, knowledge management and utilization of SPMW have great significance.

In addition, the FSPMW scheduling is a dynamic process with many time-varying factors. The data in the physical workshop cannot be fed back to the information space in a timely-manner, which does not guarantee the practicality of the scheduling plan and seriously affects productivity. Digital twin (DT) is a new technology that facilitates the interactive integration of physical and virtual spaces [3]. It has been broadly adopted in the control, operation, and optimization of intelligent production lines [4]. Applying DT to the FSPMW can allocate resources more rationally, adjust and respond to scheduling plans in a timely-manner, and improve the operational efficiency of the workshop.

Thus, this paper proposes a knowledge-driven scheduling method for ship pipe manufacturing based on DT, which improves the efficiency of workshop knowledge utilization by designing a knowledge-driven scheduling model and makes the scheduling scheme more suitable for the physical FSPMW.

The rest of this paper is organized as follows: Sect. 2 reviews the research status of knowledge management and flexible workshop scheduling. Section 3 gives a knowledge-driven framework for DT FSPMW. Section 4 constructs a knowledge model and proposes a scheduling optimization method. And based on this, Sect. 5 presents a case study of FSPMW to demonstrate the effectiveness of the proposed approach. Finally, Sect. 6 concludes the paper and points out future research directions.

2 Related Works

2.1 Knowledge Management

Knowledge is the basis of intelligent manufacturing and recent studies show that effective knowledge management and utilization can help humans make better decisions [5]. To facilitate the management of knowledge, researchers have introduced ontology into the fields of artificial intelligence, and knowledge engineering. With the arrival of Industry 4.0, ontology is increasingly used in the field of intelligent manufacturing knowledge management [6]. Zhu, Z. et al. constructed semantic graphs with semantic records of ontology storage concept data models to achieve efficient management of various scheduling data [7]. France-Mensah, J. et al. proposed an ontology of integrated information for cross-functional and spatiotemporal planning of road projects [8]. Psarommatis, F. et al. used a knowledge-based method to detect defects, enhancing the adaptability and effectiveness of automated decision-making in production systems [9].

2.2 Flexible Workshop Scheduling

The flexible job-shop scheduling problem (FJSP) is a typical scheduling problem that has been proven to be an NP-hard problem. And Li, X.'s study showed it is still a research hotspot [10]. The solutions to FJSP include mathematical programming methods, heuristics, meta-heuristics, and machine learning methods [11]. Recently, numerous researchers have made in-depth studies on FJSP and showed that swarm intelligence optimization algorithms are the mainstream algorithms for solving it [12], including genetic algorithm (GA) [13], particle swarm optimization (PSO) [14], migratory bird algorithm (MBO) [15], etc. Combining PSO and GA, Ren, W. et al. proposed a multi-objective optimization of energy-aware FJSP, achieving the improvement of the system's performance [14]. Al Aqel, G. et al. proposed an improved iterative greedy algorithm to handle FJSP and verified the feasibility of the method experimentally [16]. The Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) has been applied to various scheduling problems successfully. Luo, C. et al. proposed an energy-saving strategy based on MOEA/D and solved the scheduling problem of distributed flow shop [17]. Zhang, J. et al. demonstrated the competitiveness and effectiveness of the MOEA/D in solving scheduling problems by applying it to a power system [18]. ZHANG, W. et al. compared the operational efficiency of various algorithms in solving the FJSP, in which MOEA/D has better distributivity and the highest operational efficiency [19]. From these studies, the implementation of workshop scheduling by the MOEA/D is worth researching.

It can be seen that most of the research on the SPMW job scheduling takes the workshop job assignment as the entry point directly. Few studies focus on the knowledge utilization of SPMW, and studies about the combination of DT and job

scheduling of SPMW are rare. Therefore, this paper combines DT with SPMW job scheduling and proposes a knowledge-driven scheduling method for the FSPMW.

3 Digital Twin-Enabled Framework for FSPMW

The digital twin-based framework for FSPMW as shown in Fig. 1 is composed of three layers: the physical layer, the virtual layer, and the scheduling optimization layer.

Physical Layer: The physical SPMW consists of industrial robots (mainly 6-axis), material resources (pipes, flanges, etc.), transfer lines, etc. It generates and collects real-time data on the production status, enables data support for the performance of other units, and adjusts production actions according to control commands.

Virtual Layer: The virtual layer enables real-time mapping and supports real-time status monitoring of the physical workshop. It completes the collection of dynamic data of the physical SPMW. In addition, the DT model coordinates the optimization of the workshop scheduling strategies by simulating the scheduling process.

Scheduling Optimization Layer: Based on the DT data, by analyzing the workshop scheduling resources, this layer comes up with a more appropriate workshop scheduling scheme and realizes the optimization of workshop scheduling decisions.

In this framework, the client’s service request is sent directly to the scheduling optimization layer. And based on the knowledge and data from physical SPMW, the scheduling optimization layer generates a new scheduling scheme for the demand.

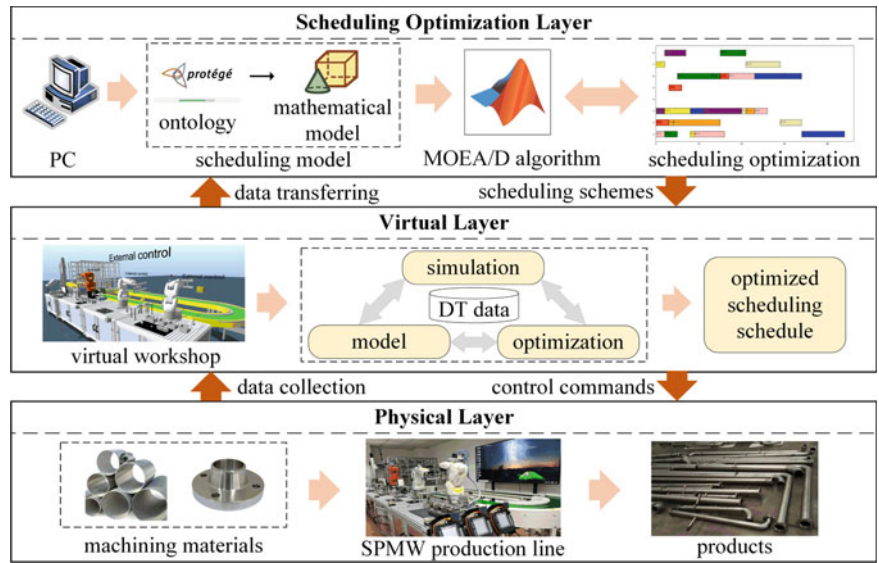


Fig. 1 The digital twin-enabled framework for FSPMW

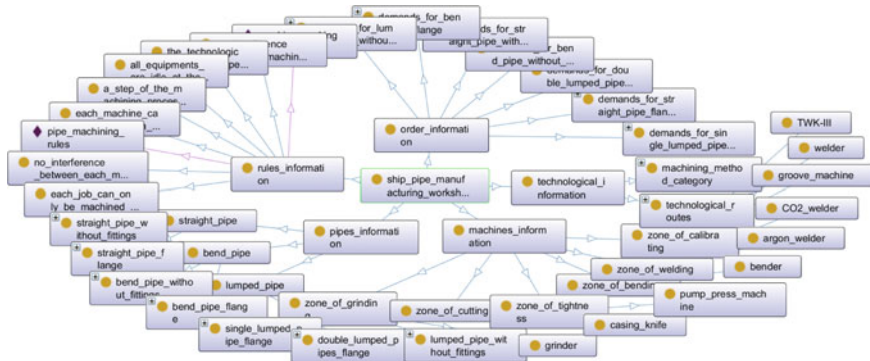


Fig. 2 The ontology model of SPMW

This scheme is then transferred to the virtual layer, where it is simulated and optimized with the DT model. Finally, the virtual layer transfers the scheduling scheme obtained by iterative optimization to the physical SPMW, achieving real-time adjustment of the physical workshop production and improving the productivity of the FSPMW.

4 Knowledge-Driven FSPMW Scheduling Method

4.1 SPMW Ontology Modeling

In the SPMW, the common manufacturing process involves six operations: cutting, bending, calibrating, welding, grinding, and tightness testing [1]. And much knowledge is involved in this process and requires effective management. Thus, Protégé, as an ontology design tool, is used to construct the SPMW's knowledge model as Fig. 2. The workshop knowledge composes of factual knowledge (FK) and rule-based knowledge (RK). And FK consists of production sources knowledge which involves pipes, machines, and orders of demands, including data attributes, object attributes, base descriptions, etc. RK involves various production constraints and rules, including historical experience, general constraints, procedure rules, decision rules, etc.

4.2 Knowledge-Driven FSPMW Scheduling Model

Problem description. In SPMW, machining tasks are low-volume and multi-variety, and a task contains multiple operations which require multiple robots to complete. With the diverse manufacturing capabilities of robots, there are multiple optional

machines for each operation, which increases the flexibility of machining and the complexity of the problem, showing that the SPMW problem is an NP-hard problem.

In the SPMW, there are J pipes ($J_1, J_2, \dots, J_J$) to be machined on m robots ($M_1, M_2, \dots, M_m$). Each pipe has multiple operations, and the sequence of the operations is strictly defined. Each operation has multiple optional machines, and the machining time differs by machine. Therefore, pipes and operations' efficient sequencing on machines are required. This research is to find a set of optimal decision sequences with minimizing the maximum completion time and the maximum machine load for the task.

The parameters are shown in Table 1. Where $i = 1, 2, \dots, J$, $j = 1, 2, \dots, q_i$, $k = 1, 2, \dots, m$. $J \geq 1$ and $m \geq 1$ is the total number of operations and machines, respectively. J_i is the i -th job number, and its j -th operation is O_{ij} . $q_i \geq 1$ is the operations number of J_i . M_k is the k -th machine in the available machine set. T_{ijk} is O_{ij} 's machining time on M_k , and S_{ijk} is the corresponding start time. $e_{O_{ij}}^t$ is the actual completion time of O_{ij} . D_{ijk} is the machine selection parameter in Eq. (1). It determines whether O_{ij} can be completed on M_k , and means yes when it is 1, and no otherwise.

$$D_{ijk} = \begin{cases} 1, & \text{if } O_{ij} \text{ machined on } M_k \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

To facilitate the study of the above problem, some constraints are made as follows:

- One machine can only machine one job at one time;
- One job can only be machined on one machine at one time;
- It cannot be interrupted once an operation starts;
- No idle priority between jobs, and 0 machining preparation time for each job;
- No priority constraints between jobs, but between operations of a job.

Ontology inference. To make the SPMW scheduling model more suitable for the manufacturing requirements, the Semantic Web Rule Language (SWRL) based

Table 1 Scheduling parameter setting

Parameter	Description
J_i	Pipe number
O_{ij}	Operation number
M_k	Machine number
J	Total number of pipes
m	Total number of machines
q_i	Number of operations
T_{ijk}	Machining time
S_{ijk}	Start machining time
$e_{O_{ij}}^t$	Completion time
D_{ijk}	Machine selection judge

inference rules are set with the ontology model to obtain the constraints of demands, as shown in Table 2. As rule 1 indicates when the demand for straight pipes without fittings is greater than 0, the machining procedure of such pipe is connected to the demand.

Based on the instances of demands, the ontology is reasoned by SWRL rules via the built-in inference engine of Drools [5] in Protégé, and the corresponding machining methods and constraints are obtained. As shown in Fig. 3, when the demand for bends is 0, the matching properties do not change after inference, while the demand for bends with flanges is greater than 0, the corresponding machining procedure, machine working rules, and pipe machining rules can be obtained.

Scheduling model. To minimize the maximum completion time and the maximum machine load of the SPMW job scheduling, the objective functions are set as follows:

- The minimized maximum completion time F_1 is defined as:

$$F_1 = \min \left(\max \left\{ e^t_{O_{ij}} \right\} \right)$$

(2)

- The minimized maximum machine load F_2 is defined as:

$$F_2 = \min \left(\max \left\{ \sum_{i \in n} \sum_{j \in m} T_{ijk} D_{ijk} \right\} \right)$$

(3)

Table 2 SWRL rules for inference

Rule 1	<code>Demands_for_straight_pipe_without_fittings(?m) ^ number_of_demands(?m, ?n) ^ route1(?p) ^ technological_route(?p, ?q) ^ swrlb:greaterThan(?n, 0) -> technological_route(?m, ?q)</code>
Rule 2	<code>Demands_for_straight_pipe_flange(?m) ^ number_of_demands(?m, ?n) ^ route2(?p) ^ technological_route(?p, ?q) ^ swrlb:greaterThan(?n, 0) -> technological_route(?m, ?q)</code>
Rule 3	<code>Demands_for_bend_pipe_without_fittings(?m) ^ number_of_demands(?m, ?n) ^ swrlb:greaterThan(?n, 0) ^ rules_information(?j) -> has_machining_rules(?m, ?j)</code>
Rule 4	<code>Demands_for_straight_pipe_flange(?m) ^ number_of_demands(?m, ?n) ^ swrlb:greaterThan(?n, 0) ^ rules_information(?j) -> has_machining_rules(?m, ?j)</code>
...	

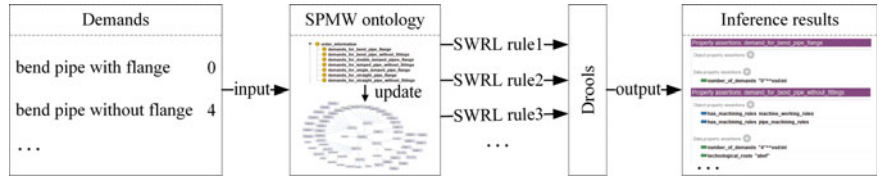


Fig. 3 The ontological inference results

The constraints obtained from the ontological inference are shown as follows:

$$\sum_{k \in m} D_{O_{ij}k} = 1 \quad (4)$$

$$e'_{O_{ij}} - \sum_{k \in m} D_{O_{ij}k} T_{ijk} = S_{ijk} \quad (5)$$

$$S_{ijk} + \sum_{k \in m} D_{O_{ij}k} T_{ijk} \leq S_{i(j+1)k} \quad (6)$$

where Eq. (4) indicates that all jobs' operations can be machined only 1 time on machines. Equation (5) shows that the operation cannot be interrupted once it has started. Equation (6) restricts the job machining sequence.

4.3 Digital Twin-Based FSPMW Scheduling Method

MOEA/D [20] is a typical multi-objective optimization algorithm with strong search capability, efficient fitness evaluation, and great convergence speed. By introducing a hybrid aggregation approach, an improved Multi-objective Evolutionary Algorithm Based on Decomposition (IMOEA/D) is designed to solve the scheduling problem of FSPMW as shown in Fig. 4.

Initialization. A combination of random and optimal machine selection is performed to initiate the population Pop with P individuals based on the FSPMW jobs. Generate P uniformly distributed weight vectors λ in the objective space by

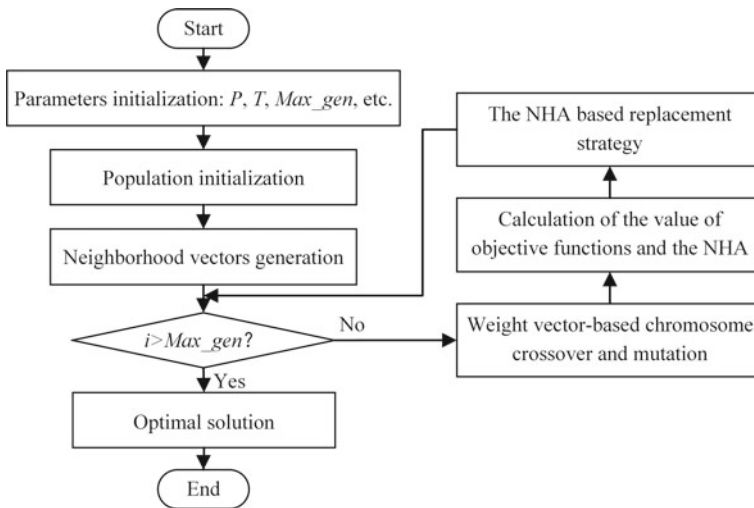


Fig. 4 The flowchart of the IMOEA/D algorithm

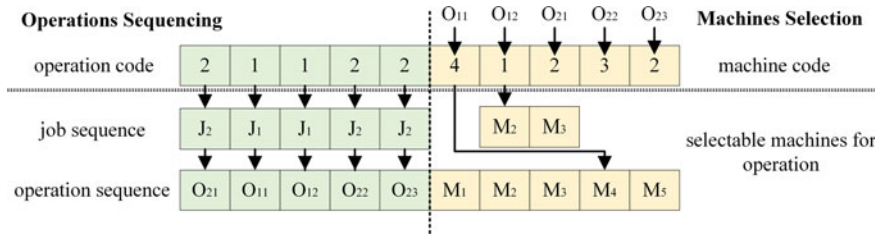


Fig. 5 Encoding

using the simplex algorithm. Then, evaluate the Euclidean distance between each two weight vectors, select the closest T ones as its neighbors, and set the maximum iteration as Max_gen .

Encoding and decoding. Each individual in the population is a machining scheme, which is coded as Fig. 5. The chromosome consists of two parts: the operation sequence (OS) and the machine selection (MS). The OS can be seen in the left half of Fig. 5, each gene is directly encoded with a job number, and the appearance order of jobs in the chromosome indicates the machining order. As the first 2 in the OS represent O_{21} , and the second 2 represent O_{22} . 2 appears three times in the OS indicating that J_2 has 3 operations. The MS is in the right half of Fig. 5, the genes are arranged in the original order of job operations and represent the sequence code of the machine selected for operations. Just as the 4 in MS represents the machine with the fourth position in the set of alternative machines is selected to complete O_{11} .

Crossover and mutation. For the chromosome crossover, the POX crossover [21] is performed in the part of the pipe operations sequencing, and the uniform crossover [21] is applied in the part of machine selection. And for the chromosome mutation, the part of operations sequencing is changed by Swap Mutation [21], which randomly swaps genes at two positions to achieve mutation operations. The part of machine selection is altered by Scramble Mutation [21], which randomly selects the machine code corresponding to a certain operation of jobs and disrupts the genes in it.

Parent update mechanism. Three traditional aggregation methods are commonly used: the Tchebycheff (TCH) approach, the weighted sum (WS) approach, and the penalty-based boundary intersection (PBI) approach [20]. Among them, the TCH approach focuses on local search, the WS approach concentrates on global search, and the PBI approach enables the algorithm to have a more balanced search performance. Thus, this paper combines these three aggregation methods and adds α , β , and γ as the proportional control parameters to form a new hybrid aggregation (NHA) method as shown in Fig. 6. It can enhance the search capability and improve the performance of the algorithm. And the NHA approach can be described as:

$$\text{ming}^{NHA} = \alpha \max_{1 \leq i \leq q} \{ \lambda_i |f_i(x) - z_i^*| \} + \beta \sum_{i=1}^q \lambda_i f_i(x) + \gamma \min(d_1 + \theta d_2) \quad (7)$$

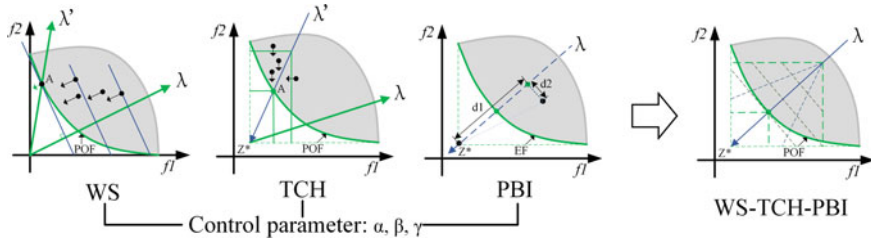


Fig. 6 The new hybrid aggregation approach

where the sum of α , β , and γ is 1, and their values are non-negative numbers that are not greater than 1. d_1 and d_2 can be described as follows:

$$\begin{cases} d_1 = \|(f(x) - z^*)^T \lambda\| / \lambda \\ d_2 = \|f(x) - (z^* + d_1(\lambda / \|\lambda\|))\| \end{cases} \quad (8)$$

where $z^* = (z_1^*, z_2^*, \dots, z_n^*)^T$ represents the reference point, and $z_i^* = \min\{f_i(x)\}$. λ represents the weight vector, q is the number of objective functions, θ is a penalty parameter, x is a set of decision variables, and $f(x)$ represents the objective function.

After the crossover and mutation are completed and new children are obtained, the IMOEAD performs replacement actions to generate a new parent based on the NHA. It iterates until the maximum iteration is reached, and the obtained nondominated solution is output as the approximate solution of the FSPMW scheduling problem.

5 Case Study and Performance Analysis

To verify the effectiveness of the FSPMW scheduling method proposed, experiments on the production of straight and bend pipes of an SPMW production line are performed as a case study. Assuming that there are 6 machines available in the FSPMW, the customer needs 10 pipes of which half is straight and the other is bent. The production of straight pipes involves 5 operations and the bend pipes require 6 operations, and the machining procedure is shown in Fig. 7. The machining operations and corresponding manufacturing time are shown in Table 3

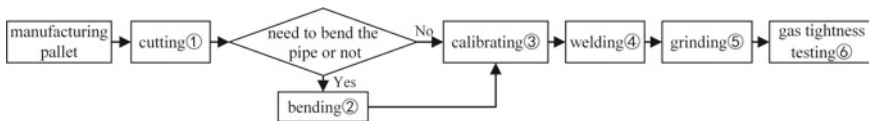


Fig. 7 The machining procedure of pipes

Table 3 The order information

Job	Operation	Machining time					
		M_1	M_2	M_3	M_4	M_5	M_6
J_1	O_{11}	9	-	8	-	-	-
	O_{12}	-	6	9	-	7	-
	O_{13}	-	-	8	-	-	6
	O_{14}	7	10	-	-	-	9
	O_{15}	-	-	6	-	-	-
	O_{16}	-	-	10	7	-	10
J_2	O_{21}	-	-	-	-	8	-
	O_{22}	-	-	6	-	-	-
	O_{23}	6	-	-	-	-	-
	O_{24}	-	-	-	10	9	-
	O_{25}	5	10	-	-	-	9
...							

With the customer’s demand input into the knowledge model, the manufacturing constraints corresponding to the pipes are obtained. And based on this, the IMOEA/D is applied to optimize the production schedule of the SPMW. The *Pop* size P of IMOEA/D is 200, the number of neighbors is $P/5$, and the *Max_gen* is 250. According to several experiments, the best solution was found when the parameters were set as Table 4.

And to observe the two objective functions’ global trends during iterations, a weighted sum of them is considered as fitness, as shown in Eq. (9). Since both are equally important, the weight parameter w is set to 0.5. And the smaller the fitness value, the better the current population. The output of the algorithm is the schedule corresponding to the optimal fitness of the SPMW, and it is shown in Fig. 8. One color represents one pipe, and the colored fields represent the performing time of the operation marked in them. And the *J1-1* represents O_{11} .

$$Fitness = (1 - w)F_1 + wF_2$$

(9)

To verify the effectiveness of the designed IMOEA/D, it is compared with the improved migratory bird algorithm (IMBO) proposed by LIU, X. [15] and the improved genetic algorithm (IGA) proposed by Zhang, G. [13]. The fitness curves for each population are shown in Fig. 9. The IMOEA/D has a significant benefit over the

Table 4 Parameters value setting

Parameter	Crossover rate	Mutation rate	θ	α	β	γ
value	0.8	0.5	0.12	0.5	0.3	0.2

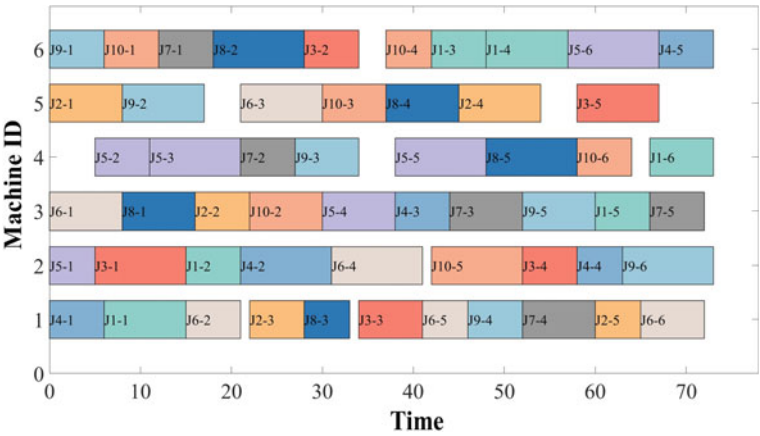


Fig. 8 The Gantt chart of the FSPMW job scheduling

other algorithms in 250 iterations. In 20 iterations, the fitness of the MOEA/D-TCH is slightly lower than the IMOE/D, while in 21 to 250 iterations, the IMOE/D outperforms the other algorithms and enters convergence at the 122nd iteration, and its fitness ends up converging at a lower point than the other algorithms. It can be concluded that IMOE/D performs better than IMBO and IGA.

The optimal results are shown in Table 5. It can be seen that the IMOE/D has better the optimal solution and the smallest fitness than others, which shows the application of IMOE/D in FSPMW scheduling more effectively than other algorithms.

As the production situation of the FSPMW changes, the DT platform senses the real-time workshop production information, identifies the changed data, and

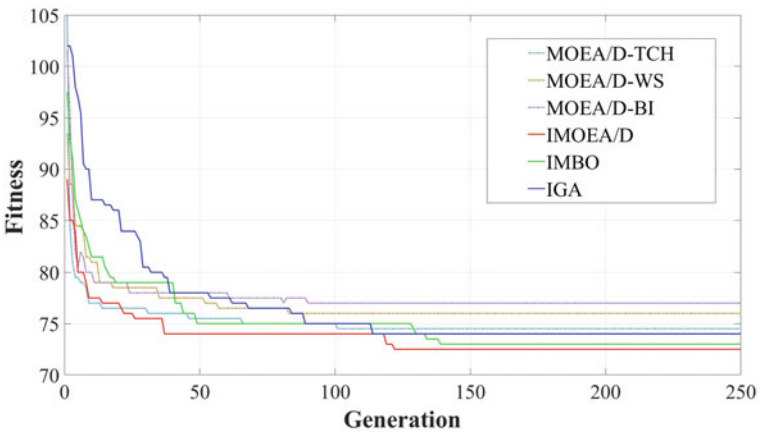


Fig. 9 The fitness curves

Table 5 Results comparison

Algorithm	MOEA/D-TCH	MOEA/D-WS	MOEA/D-BI	IMOEAD	IMBO	IGA
Optimal solution	(78,72)	(78,74)	(78,76)	(73,72)	(73,73)	(75,73)
Optimal fitness	74.5	76	77	72.5	73	74

transmits it to the knowledge model. The scheduling model is adjusted and applied to the IMOEAD to obtain a new scheduling solution that fits the real-time situation of the FSPMW.

6 Conclusion

In this paper, DT is introduced to the framework of FSPMW job scheduling, and a DT-based dynamic scheduling mechanism is proposed. A knowledge-driven method is proposed to construct the scheduling model. Based on this, a scheduling optimization method with IMOEAD is proposed to solve the FSPMW scheduling problem. In the future, the knowledge-driven model requires refinement, and the FSPMW scheduling under uncertainty needs further research and exploration.

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Impact of Incentive Policies on the Profitability of Manufacturers and Third-Party Remanufacturers in the Circular Economy



Xiaomei Sun and Chao Wang 

Abstract In the realm of remanufacturing, the strategic choice of globalization stands at a crossroads, promising technological leaps, enhanced value creation, and broader opportunities. This study unveils a sophisticated model that scrutinizes the impact of incentive policies, with a focus on outsourcing subsidies, on the financial outcomes of manufacturers and third-party remanufacturers within the circular economy. Incorporating variables such as pricing strategies, remanufacturing capacity, and warranty costs, the model sets forth distinct objectives and constraints for both parties. The findings highlight the profound influence of these incentives on profitability dynamics. While manufacturers have the potential to amplify both the remanufacturing market and their profit margins through judicious use of these incentives, the success of such endeavors hinges on factors like market demand, astute pricing, and cost optimization. The research delineates three plausible scenarios: (1) manufacturers facing downturns while third-party remanufacturers prosper, (2) a win-win profitability scenario, or (3) a challenging landscape with losses for both. To navigate these outcomes and ensure effective policy implementation, a deep understanding of market intricacies and strategic cost management is paramount. In essence, this study accentuates the importance of meticulously designed policies and decision-making tools in fostering a resilient circular economy and sustainable progression, serving as a beacon for industry stakeholders.

Keywords Circular economy · Remanufacturing · Profitability · Decision support

X. Sun · C. Wang (✉)

School of Business, Suzhou University of Science and Technology, Suzhou 215009, China

e-mail: cslgew@usts.edu.cn

X. Sun

e-mail: ustssxm@usts.edu.cn

1 Introduction

The circular economy has become a prominent strategy for achieving sustainable development amidst current global environmental concerns. In the realm of the circular economy, manufacturers stand as the initiators. They design, produce, and launch new products, ensuring top-notch quality and sustainability from the get-go. However, the product journey doesn't end with its initial use. This is where third-party remanufacturers come in. They take used products and analysed rejuvenate them, making them market-ready once again. It's a partnership of creation and rejuvenation: manufacturers set the stage with innovative products, and remanufacturers ensure these products get a renewed life, fostering sustainability. Together, they form a cohesive, efficient system that epitomizes the principles of the circular economy, ensuring resources are used wisely and products live longer, more purposeful lives. Concepts like closed-loop supply chains and remanufacturing have gained widespread attention in this context, with government incentives playing a critical role in promoting the profit sustainability of manufacturers and third-party remanufacturers within closed-loop supply chains.

Recent research has shed light on the closed-loop supply chain models for sustainable production and remanufacturing. Scholars have noted that these models provide a sustainable solution for production and remanufacturing processes, and offer guidance in understanding the importance of circular economy and the potential of closed-loop supply chains [7]. The level of environmental concern among consumers plays a significant role in determining their acceptance and willingness to pay for remanufactured products. This, in turn, affects the profits of manufacturers and third-party remanufacturers involved in closed-loop supply chains [2]. Xu et al. conducted a study on the influence of carbon tax policies on pricing decisions and coordination mechanisms in closed-loop supply chains. The study highlights the significant relationship between consumer analysed and the circular economy, revealing the crucial impact of carbon tax policies on the profit sustainability of manufacturers and third-party remanufacturers [9]. Xu et al. conducted a study on the impact of government subsidies and emission reduction requirements on closed-loop supply chains. Their research highlights the importance of government policies in promoting collaboration between manufacturers and third-party remanufacturers in the circular economy [8].

The profit sustainability of manufacturers and third-party remanufacturers in closed-loop supply chains is influenced by factors such as corporate social responsibility and green marketing. The study revealed that considering corporate social responsibility has a significant impact on the profit sustainability of manufacturers and third-party remanufacturers, while also promoting the development of the circular economy [5]. Song et al. investigated the effects of government subsidies and recycling targets on closed-loop supply chains. They found that these policies can have a significant impact on the coordination and collaboration between manufacturers and third-party remanufacturers, ultimately contributing to the growth of the circular economy [6]. Meng et al. conducted a study on coordination issues in

closed-loop supply chains with third-party collection, taking into account government subsidy strategies. Their findings suggest that government subsidies can incentivize the participation and collaboration of third-party re-manufacturers, ultimately leading to the realization of a circular economy [4]. Chen et al. investigated the correlation between green marketing and consumers' willingness to pay for remanufactured products. They emphasized the influence of green marketing on consumers' acceptance and willingness to pay, which ultimately affects the profitability of both manufacturers and third-party remanufacturers [1]. Maiti conducted a study on the most effective production and pricing strategies for manufacturers operating in closed-loop supply chains with third-party remanufacturing. The study revealed that the production and pricing strategies adopted by manufacturers have a significant impact on profit sustainability, particularly when third-party remanufacturers are involved [3].

The circular economy can be promoted through various factors such as government incentive policies, consumer analysed, corporate social responsibility, carbon tax policies, government subsidies, and green marketing. These factors are important in facilitating resource recovery and reuse, and can contribute to the development of closed-loop supply chains that promote sustainable development. To effectively promote the circular economy, it is important to understand and apply these insights in the formulation of incentive policies. In addition, it is crucial to address the interaction and profit optimization problem between manufacturers and third-party remanufacturers under incentive policies for successful implementation of the circular economy. This study aims to address this issue and contribute to the promotion of sustainable development. In this study, two models were established and analysed separately in Sects. 2 and 3. The results indicate that by offering outsourcing subsidies, as well considering the prices for new products and the remanufactured ones, both parties could have higher profits. However, it is important to take into account market factors and optimize costs to achieve desired outcomes and promote sustainable development.

2 Basic Outsourcing Service Model

2.1 *The Establishment of the Basic Outsourcing Service Model*

The proposed model aims to enhance decision-making in the remanufacturing industry for two key stakeholders: the manufacturer and the third-party remanufacturer. The model assumes that the manufacturer does not engage in remanufacturing, and also considers scenarios where remanufacturing is a separate division of an existing car manufacturer. The manufacturer sets the unit retail prices of new and remanufactured products, and determines the remanufacturing capacity. The objective of the manufacturer is to maximize profit while considering the cost of warranty,

cost of the remanufacturing and demand for both new products and remanufactured products. Moreover, the total market demand D is the sum of the demand for new products D_n and the demand for remanufactured products D_r .

The third-party remanufacturer aims to obtain an appropriate resale price P_r for remanufactured products and reduce the expenses of remanufacturing c while maximizing profit. They take into consideration the cost of remanufacturing, the demand for their products, and the expenses associated with enhancing the quality of their re-manufactured products.

The proposed model takes into account several constraints simplified, ensuring that the total market demand is equal to the demand for new and remanufactured products combined. The demand for remanufactured products is assumed to be a proportion of the demand for new products which could be set by the manufactures. The model also considers the warranty cost provided by the manufacturer for each unit of new products. By optimizing these decision variables while considering the constraints, the proposed model aims to facilitate effective decision-making in the remanufacturing industry, taking into account the perspectives of both manufacturers and third-party remanufacturers.

Hence, the objective function to maximize profit for the manufacturer and the third-party remanufacturer were listed as Eqs. 2 and 3 as below:

$$\pi_1 = (P_n - m - k)D_n - cD_r \tag{1}$$

$$\pi_2 = P_r D_r - bD_r + cD_r \tag{2}$$

Here, b signifies the remanufacturing cost parameter specific to third-party manufacturers, whereas c indicates the remanufacturing cost parameter extended by the original manufacturer for third-party remanufacturers. The description of the symbols involved in the above equations is shown in Table 1, and the three potential profit outcomes for both parties is shown in Table 2.

Table 1 The description of the symbols used in the model

Symbol	Description
D_n	Market demand for new products
D_r	Market demand for remanufactured products
D	Total market demand
P_n	Unit retail price of new products
P_r	Unit retail price of remanufactured products
m	Comprehensive cost of the new product
c	Subsidy from Manufacturer to Remanufacturer
P_r	Unit retail price of remanufactured products
b	Remanufacturing cost parameter for third-party remanufacturers
k	Warranty cost parameter

Table 2 Three potential profit outcomes for both parties

Scenario	D_n	D_r	c	π_1	π_2
1	9000	1000	5	625,000	75,000
2	5000	5000	50	100,000	600,000
3	8000	2000	25	510,000	190,000

2.2 Analysis of the Basic Outsourcing Service Model

The remanufacturing industry's profitability is a crucial concern for both manufacturers and third-party remanufacturers. The basic outsourcing service model generates various scenarios based on the involved variables. Given the assumptions as below:

- $P_n = 180$
- $P_r = 120$
- $m = 100$
- $b = 50$
- $k = 10$
- $D_n + D_r = 10,000$

1. Manufacturer Profits, Third-Party Remanufacturer Suffers Losses

In this scenario, the manufacturer shows a significant profit, indicating that they have a strong market share with a high demand for new products ($D_n = 9000$). The unit price for remanufactured products is 120, and the third-party remanufacturer also makes a profit, but it's significantly lower than the manufacturer's. The subsidy or remanufacturing cost parameter offered by the manufacturer to the third-party remanufacturer (c) is relatively low at 5, which means the manufacturer does not heavily subsidize the third-party remanufacturer, allowing for a larger profit margin for the manufacturer.

2. Third-Party Remanufacturer Profits, Manufacturer Suffers Losses

Here, the tables turn with the third-party remanufacturer achieving profitability while the manufacturer faces losses. This outcome stems from the adjusted retail price of new products, now set at a reduced \$150, paired with the higher remanufacturing cost the manufacturer incurs. Simultaneously, the third-party remanufacturer benefits from a retail price for remanufactured products that's closer to the new product price, coupled with the subsidy they receive, resulting in a profitable outcome for them. Here, there's an equal demand for new and remanufactured products. The remanufacturing cost parameter is considerably high ($c = 50$), indicating a substantial subsidy or cost-sharing between the manufacturer and the third-party remanufacturer. This scenario shifts the profit heavily in favor of the third-party remanufacturer. The manufacturer's profit is significantly less in comparison, but this structure promotes a thriving third-party remanufacturing market.

3. Both Manufacturer and Third-Party Remanufacturer Profit

In this case, the manufacturer still retains a strong market share with 8000 units of new product demand. However, the subsidy or remanufacturing cost parameter (c) has increased to 25, suggesting a more balanced support system between the manufacturer and the third-party remanufacturer. Profits for both parties are substantial, with the manufacturer leading but not overshadowing the third-party remanufacturer. This represents a balanced market scenario where both new products and remanufactured products have their distinct places, and both the manufacturer and third-party remanufacturer can operate profitably.

The scenarios discussed above are based on the model's assumptions and specific combinations of variables. However, in practical settings, the profitability of the remanufacturing industry is influenced by various additional factors that must be carefully considered during decision-making processes. From the above three scenarios, it is evident that establishing a mathematical model to assist manufacturers in setting a reasonable retail price for new products, remanufactured products, the proportion of remanufactured products, and the remanufacturing subsidy is crucial for ensuring the profitability of both parties.

3 Mathematic Modeling

3.1 The Development of Model

From the foundational model presented in the preceding section, it's evident that, even with numerous constants, multiple scenarios can emerge concerning the profit dynamics between the manufacturer and the third-party remanufacturer. To inject further nuance into this model, we've adjusted the total product sales volume to be intrinsically linked to the new product's sale price as shown in Eq. 3. Additionally, the remanufacturing cost (b) has been redefined to reflect its correlation with the subsidy magnitude (c) as shown in Eq. 4.

$$D = \frac{D_0}{e^{-\alpha(p_n - p_0)}} \quad (3)$$

$$b = m - \beta \log(c + 1) \quad (4)$$

where, D_0 represents the ideal total market demand for the product, α and β represent the scale factors respectively. Additionally, considering the dominant position of the manufacturer in profits, the manufacturer's profit being greater than the third-party remanufacturer's profit has been set as a boundary condition.

Firstly, the model primarily aims at profit maximization, with the objective function as shown in Eq. 5. Simultaneously, it considers the selling price of new products,

the selling price of remanufactured products, the quantity of remanufactured products, and the subsidy provided by the manufacturer to the third-party remanufacturer as variables to be solved for. Based on the computed results, further discussions and analysis will provide valuable recommendations for the manufacturer to set reasonable prices, determine remanufactured product shares, and establish subsidies.

$$\pi_1 + \pi_2 = (P_n - m - k)(D - D_r) + (P_r - b)D_r \quad (5)$$

The assumed conditions used during the model optimization process are as follows:

- $D_0 = 10000$
- $m = 100$
- $\alpha = 0.01$
- $\beta = 10$

3.2 The Optimization Results

To address the aforementioned problem, and mindful of the computational complexity involved, this study utilized the basic Bees Algorithm (BA) for solving it. As shown in the Fig. 1, after 100 iterations, the maximum profit obtained is 802,229, of which 341,714 is the profit from remanufacturing. The corresponding solution was shown in Table 3. The algorithm suggests a remanufactured product quantity of 3,242 units when the total product sales are 10,202 units. At the same time, the suggested prices for new products and remanufactured products are 178 and 130 respectively, with a recommended subsidy of 22. It should be noted that this suggestion is obtained with the objective of maximizing the combined profit of both parties. If further alignment with both parties' profit expectations is needed, additional profit distribution should be conducted.

3.3 Analysis of the Mathematic Model

The profitability of a manufacturer hinges predominantly on the pricing of new products, their production costs, the demand dynamics for remanufactured items, and the subsidies extended to remanufacturers. Conversely, a remanufacturer's earnings are shaped by the pricing strategy for remanufactured goods, their associated costs, and the subsidies they garner from manufacturers. Notably, as subsidies rise, the cost burden on remanufactured products lightens, amplifying the remanufacturer's profit margins.

Manufacturers can bolster their profit margins by either elevating the price points of new products or streamlining production costs. Additionally, they can engage

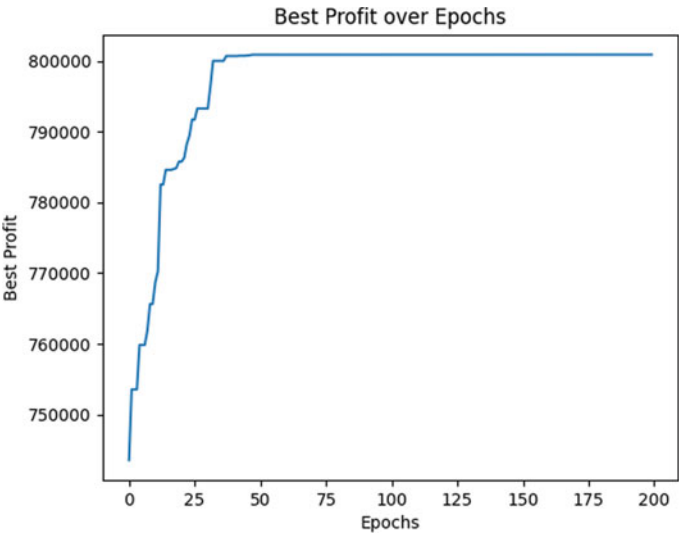


Fig. 1 The best profit over epochs

Table 3 The optimized solution

Parameter	Value
D_r	3242
P_n	178
P_r	130
c	22.3

in negotiations with remanufacturers to recalibrate subsidy allocations. Remanufacturers, on the other hand, can enhance profitability by optimizing the pricing of remanufactured goods, refining cost structures, or seeking more avourable subsidy terms from manufacturers. To ensure a win–win, open dialogue and strategic negotiations between manufacturers and remanufacturers are of paramount importance. For instance, after establishing the profit objectives for both parties, one can optimize the selling price of new products, the price of remanufactured products, the proportion of remanufactured products, and subsidies to first achieve mutual profit maximization. Building on this foundation, further adjustments to the subsidies can ensure that the profit goals of both parties are met.

4 Conclusion

Insights from the Basic Outsourcing Service Model: This model serves as a pivotal tool for informed decision-making within the remanufacturing sector. By encompassing both the manufacturer's and third-party remanufacturer's viewpoints, it delineates the nuances of optimizing retail prices, determining remanufacturing capacities, and setting appropriate subsidy levels. The various scenarios presented underscore the intricate balance that ensures mutual profitability, highlighting the critical role of pricing, remanufacturing costs, demand patterns, and subsidies in shaping the industry's profit landscape.

Strategic Collaboration for Profit Goals: Optimization results indicate that both parties should initially strive for profit maximization without considering remanufacturing subsidies. Once this is achieved, they can then adjust the remanufacturing subsidy or employ other forms of profit transfer to realize their individual profit objectives. This approach underscores the importance of a phased strategy, where initial efforts focus on collective gains, followed by tailored adjustments to meet specific profit aspirations.

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Analysis of Strategies and Models for Industrial Symbiosis in Manufacturing Ecosystems



Valentina Di Pasquale , Mario Caterino, Stefano Riemma, Marta Rinaldi, Fabio Fruggiero, and Raffaele Iannone

Abstract In the coming decades, a primary challenge for the global economy lies in reconciling economic growth with environmental sustainability and the responsible consumption of natural resources. The transition from a linear economy to a circular one has gained recognition as a pivotal strategy for achieving net-zero greenhouse gas emissions. Industrial Symbiosis (IS) emerges as a crucial tool in this transition, fostering a circular economy at both national and global levels. IS represents an innovative approach to minimize raw material extraction and optimize resource utilization. Despite recognized environmental, economic, and social benefits, various barriers hinder IS implementation, particularly in manufacturing environments and few detailed case studies in scientific literature have been reported. This study aims to bridge this knowledge gap by systematically analyzing 16 selected articles on IS in manufacturing systems. The analysis categorizes case studies by various parameters, including publication year, manufacturing sector, country, entities involved, IS network characteristics, and exchange methods. It also highlights key trends, barriers, and drivers for IS implementation. The study reveals an increasing interest in IS since 2011, emphasizing its potential to address sustainability challenges while fostering economic growth. It underscores the importance of clear legislation, economic incentives, and knowledge dissemination to facilitate IS adoption. In conclusion, industrial symbiosis and the circular economy are vital strategies to achieve sustainable resource management and economic resilience. Overcoming barriers and promoting IS practices are essential steps towards a more sustainable future.

Keywords Circular economy · Industrial systems · Industrial symbiosis

V. Di Pasquale (✉) · M. Caterino · S. Riemma · R. Iannone
Department of Industrial Engineering, University of Salerno, 84084 Fisciano, Italy
e-mail: vdipasquale@unisa.it

M. Rinaldi
University of Campania, 81031 Aversa, Italy

F. Fruggiero
School of Engineering, University of Basilicata, Potenza, Italy

1 Introduction

In the upcoming decades, one of the primary challenges facing the global economy will revolve around the disconnection between economic growth, environmental impact, and the consumption of natural resources. To face this challenge, it will be necessary to adopt industrial strategies and policies that promote a more efficient use of resources, mitigating the excessive anthropogenic pressure on biodiversity, ecosystems, and the services they provide. The development of a circular economy as a key strategy to achieve net-zero greenhouse gas emissions has gained recognition from an ever-expanding group of nations. The shift from a linear economy to a circular economy within the industrial sector holds the potential to enhance global economic resilience. Within this framework, Industrial Symbiosis (IS) emerges as a key tool to support the transition towards the circular economy, both on a national and global scale. It can be regarded as an innovative and essential tool for reducing the extraction of raw materials and optimizing their utilization, representing an effective and efficient approach to close the loop on resource cycles. In fact, the Circular Economy “is a development strategy that aims to minimize the withdrawal of raw materials by placing them in a continuous circle. It is a system that regenerates itself, whereby the product does not reach the end of its life cycle because it is reused”. However, for an effective transition to a circular model, it is imperative to involve all stages of the production process, starting from the design phase and extending through to the final use of products. This necessitates a novel approach that places a strong emphasis on designing and manufacturing products that are both durable and recyclable. In this context, researchers and scholars have, over the years, recognized a profound connection between natural and industrial ecosystems [1]. The concept of eco-industrial systems, inspired by natural ecosystems, aims to reduce waste generated in production processes and maximize the efficient use of waste materials and end-of-life products. This approach creates opportunities for other production processes. Activating this system requires the collaboration of multiple actors working together to address a significant set of potential problems. For Ayres [1] this collaboration was part of the biosphere/technosphere metaphor used to explore the concepts of ecology, metabolism and industrial symbiosis. According to [1], the biosphere has developed efficient methods for using materials and energy over the course of evolution. In contrast, the technosphere often exploits natural resources while generating unused by-products released into the environment, such as polluting emissions into the air, water, and soil. Drawing inspiration from the biosphere, the technosphere can design and manage its processes in a way that improves efficiency and minimizes environmental impact by limiting the release of unused by-products. An industrial analogy to an ecosystem is an industrial park that internally captures and recycles all physical materials, consuming energy only from external sources [1]. This theory was subsequently endorsed in 1997 by the United Nations Environment Programme (UNEP), which advocated for Industrial Symbiosis to foster a sustainable production system.

1.1 IS Classification

In the establishment of Industrial Symbiosis relationships, two distinct mechanisms can be identified: “emerging from below” (Bottom-up) and “designed following the top-down approach” (Top-down). In the case of bottom-up IS, the synergy between companies emerges spontaneously, without centralized planning. Companies come together organically based on common objectives, such as energy conservation and waste reduction, and begin collaborating in pursuit of these goals. Local governments can play a supportive role, for example, by offering consulting services and facilitating business relationships [2]. A well-known example is the Kalundborg eco-park in Denmark (Bottom-up): six enterprises, including an electricity generation plant, an oil refinery, a biotechnology company, a construction products company, a waste management company, and the local administration, came together out of the necessity to find an alternative solution for water supply. They initiated cooperation and derived mutual benefits through an open management style. On the other hand, “Eco-industrial parks” serve as typical examples of Top-down IS, where the synergy between companies is planned and coordinated by a central authority actively involved in creating and managing the industrial park. In this scenario, companies are selected and invited to establish themselves in the park, based on criteria defined by the central authority, such as environmental compatibility and complementarity of production activities. The central authority may also offer financial incentives and support services to businesses [2].

Industrial symbiosis can be implemented at three distinct levels: micro, meso, and macro, each referring to the boundaries within which industrial symbiosis relationships develop. The micro level pertains to the company level, where individual companies engage in symbiotic relationships. The meso level involves interactions between companies with geographical proximity, often seen in settings like eco-industrial parks. The macro level encompasses activities that occur at a regional or national scale, indicating broader industrial symbiosis initiatives [3]. Focusing on the methods of sharing resources, three different methods can be distinguished:

1. Exchange of by-products or waste: Industrial symbiosis promotes the use of by-products or waste instead of raw materials or commercial products. Through the exchange of materials that would otherwise be discarded, it is possible to enhance resource efficiency by tapping into the intrinsic economic value of waste.
2. Sharing of infrastructure or services: Industrial symbiosis strategies can be implemented by providing services (such as water, energy, heat supply systems, wastewater treatment plants, and transport) or public utility infrastructures and sharing them with a group of companies.
3. Sharing of ancillary services: Another approach involves sharing services that are not directly related to the company’s core business, such as security, cleaning, or catering services.

1.2 Driving and Facilitating Factors of Industrial Symbiosis

There are numerous factors that play a significant role in achieving synergistic relationships and realizing the expected benefits from these [3–10]:

- Knowledge and awareness of the environmental, economic, and social benefits that IS offers.
- The economic, environmental, political, and social context of a country, which can be decisive in how sustainability issues are addressed and, consequently, how they can promote or condition the development of industrial symbiosis.
- The existing legislation, plans, and policies in each country.
- The prevalence of certain types of industries within countries, especially those that are major resource consumers and greenhouse gas emitters, play a key role in economic development and have a long tradition in that country. These companies are often referred to as “anchor tenants” [11], signifying the company’s capacity to attract and establish a network of businesses, not only regarding material supply, but also for waste reuse.
- The diversity of industries has often been highlighted as a facilitator for the creation of synergistic relationships.
- The trust between companies, ensuring the supply of waste and resources in sufficient quantity and quality for the functioning of receiving companies.
- The geographical proximity between potential participants in IS.
- The existence of well-established industrial symbiosis networks in a particular location can drive the creation of new synergistic connections and the expansion of the network to new companies, as internal structures and trust relationships that facilitate this development are already established.

1.3 Purpose of the Study

Despite the well-recognized environmental, economic, and social benefits that industrial symbiosis can offer, several barriers hinder its development and diffusion, particularly in manufacturing environments [3–7, 9, 12]. Several studies in the literature have pointed out that, despite the significant potential of industrial symbiosis and the increasing number of operational cases, there are few detailed case studies published and analysed in scientific literature [5]. However, it is crucial for the industry to be aware of the potential of industrial symbiosis, not solely through theoretical studies, simulations, or encouraging legislation, but through the real demonstration of successful results. Equally important is the understanding of the existing barriers and obstacles to overcome them. To address these literature gaps and enhance understanding among researchers and businesses, this paper aims to conduct an analysis of the scientific literature on IS in manufacturing systems. Its objective is to identify trends in industrial symbiosis research and systematically review and categorize case

studies. Through these efforts, we aim to raise awareness and expand knowledge in this field, ultimately promoting the growth of industrial symbiosis practices.

2 Materials and Methods

This study is based on a systematic literature review of industrial symbiosis within manufacturing systems. The research process was divided into the following phases:

- Database search with defined limitations: a search for articles was conducted on the Scopus database in April 2023. Keywords “Industrial symbiosis” AND “Manufacturing” were used with Boolean operator (AND) in the title, abstract, and keywords fields. In the initial phase, there were no specific limitations imposed. The total number of publications obtained at this stage was 177.
- Two-step screening process: the screening process was divided into two subsequent phases. In the first screening phase, three filters were applied:
 - Time Limitation: articles published starting from the year 2000, marking the emergence of the concept of industrial symbiosis.
 - Article Type Limitation: articles not published in scientific journals (such as conference proceedings, sector reports, books, book chapters, and editorials) were excluded from the analysis.
 - Linguistic Limitation: only articles written in English were considered.

The resulting publications from this initial selection phase underwent a second screening process to identify the most relevant articles for the study. During this phase, titles, keywords, and abstracts were carefully reviewed with the objective to select articles that predominantly or significantly focused on industrial symbiosis within manufacturing ecosystems. In cases of uncertainty about whether to include an article, an analysis was conducted to assess the frequency of keywords within the publication and the context in which they were used. This analysis aimed to confirm that industrial symbiosis was indeed the primary focus of the study and not merely a means of contextualizing other concepts. Additionally, regarding case studies, it was ensured that at least one of the industries involved in the synergistic relationship or industrial symbiosis network belonged to the manufacturing sector. The entire research and selection process ultimately resulted in a total of 16 articles.

- Analysis of the chosen papers and extraction of data: the final phase of the review includes the categorization of the selected articles (publication year, journal source, type of contribution, manufacturing sector, country, number of entities involved, industrial symbiosis network and exchange modes/methods) and then the in-depth analysis of the case studies (barriers and drivers).

This methodological approach was adopted to gain a comprehensive understanding of the state of research on industrial symbiosis within manufacturing ecosystems.

3 Results

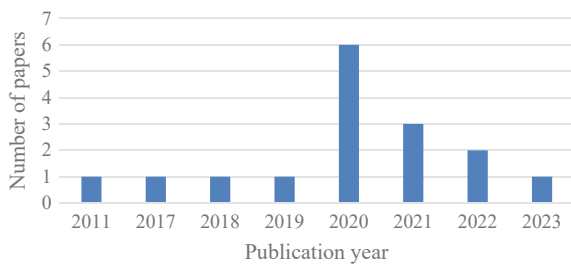
During the categorization phase, key data from the 16 selected articles were extracted. This data was collected with the intention of conducting a first analysis based on the Publication Year, Editorial Placement, and Type of Contribution.

The limited number of case studies conducted in manufacturing environments underscores the significant gap that still exists in the successful diffusion and implementation of the IS model. When comparing the results obtained in this review with those reported in other recent reviews [5], a notable discrepancy becomes apparent. This discrepancy is primarily due to the substantial number of articles published over the years that primarily propose theoretical models, conduct economic-managerial studies, or analyse the advantages and disadvantages of IS. These articles were not included in the scope of this review. Despite this limitation, the distribution of the 16 selected articles across different years highlights the increasing interest of the scientific community in industrial symbiosis (Fig. 1).

It is being increasingly recognized as a viable means to address pressing challenges, including the continuous extraction of essential raw materials, the mounting solid waste in urban and industrial settings, and the emissions of greenhouse gases into the atmosphere. Importantly, these efforts aim to achieve these sustainability goals without hindering the process of industrialization and, consequently, economic growth. The graph above underscores that only four articles were selected before the year 2019. Furthermore, the selected articles were obtained from ten different sources, and as shown in Fig. 2, the distribution of articles by journal is not uniform.

The selected articles on industrial symbiosis have been analysed and categorized (Table 1) based on their content into two primary categories: Case Studies (9 papers) and Potential Industrial Symbiosis (7 papers). The Case Studies category exhibits a wide diversity in terms of location, type of activity, methodologies employed, and the formation and development of symbiosis and are in-depth analysed in Sect. 3.1. It also includes publications that utilize qualitative data, such as interviews, to examine existing cases of industrial symbiosis. Furthermore, this category encompasses more specialized publications that concentrate on exploring novel uses of by-products or waste to fully unlock the potential of industrial symbiosis. To encompass these more focused publications, a new category, Potential Industrial Symbiosis, has been introduced. These additional articles shed light on a broad range of untapped symbiotic

Fig. 1 Publication year distribution of the selected papers



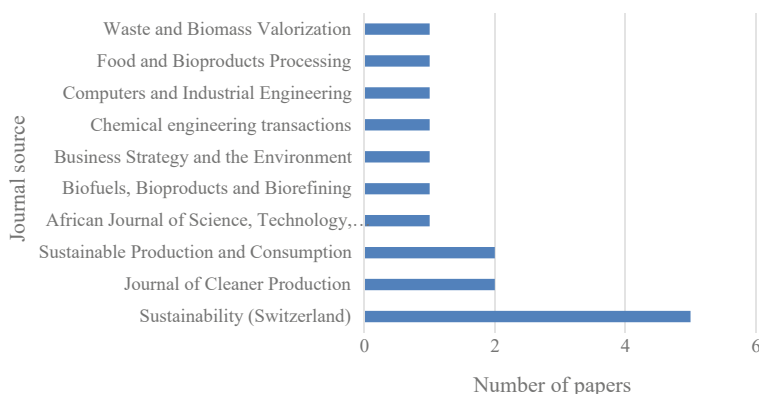


Fig. 2 Journal source distribution

opportunities, pointing out the potential for further optimization. These opportunities transcend the establishment of new symbiotic relationships between industries, extending to innovative approaches for waste utilization and the creation of new products through industrial symbiosis. Among these articles, one study stands out for proposing the initiation of an industrial symbiosis between the automotive and construction industries [13]. This concept encourages the creative repurposing of sheet metal scraps from car bodywork production to design and manufacture metal facades for buildings.

3.1 Industrial Symbiosis Network and Exchange Modes/Methods

These case studies were then examined based on their geographical location, the number of entities involved, the manufacturing sector, the nature of the exchange or sharing (Table 1). The cases of industrial symbiosis selected in the literature are spread across the globe, including both developed regions like the United States of America and developing or underdeveloped countries such as China, Brazil, and Tanzania. This demonstrates that establishing synergistic relationships can be a strategy to fully leverage the resources that these countries have to offer while also fostering sustainable economic growth. Regarding the types of industries involved, the manufacturing sector is predominant, with industries in this sector frequently serving as anchor tenants in most instances. This is because industries such as chemicals, cement, cellulose and paper, steel, oil, and energy, which are commonly found in industrial symbiosis, are highly energy-intensive and make substantial contributions to carbon dioxide emissions. This motivates endeavours to improve their efficiency and reduce the adverse effects of their production processes. In addition to the diversity in terms of location, the reported case studies also exhibit significant variation

Table 1 Selected papers

Reference	Type of contribution	Country	Manufacturing sector	Number of involved entities
[14]	Case study	USA	Additive manufacturing	4
[6]	Potential industrial symbiosis	Czech Republic	Construction	–
[15]	Case study	China	Chemical industry	128
[9]	Potential industrial symbiosis	New Zealand	Biorefinery	–
[16]	Potential industrial symbiosis	USA	Biofuels	–
[17]	Case study	Brazil	Manufacturing	8
[18]	Potential industrial symbiosis	Sweden	Manufacturing	–
[19]	Case study	USA	Construction	4
[13]	Potential industrial symbiosis	–	Automotive	–
[20]	Case study	Taiwan	Manufacturing	20
[21]	Potential industrial symbiosis	Brazil	Furniture companies	8
[22]	Case study	Tanzania	Sugar industry	4
[23]	Potential industrial symbiosis	–	Food manufacturing and biorefinery	
[24]	Case study	Brazil	Manufacturing	3
[11]	Case study	China	Sugar industry	–
[25]	Case study	Puerto Rico	Pharmaceutical	8

in the sizes and types of activities involved in industrial symbiosis. Some instances of industrial symbiosis focus on just three or four industries [14, 19, 22, 24], while other cases involve a wide array of industries, encompassing both a high number and a variety of economic activities [15, 20]. Furthermore, during the IS development, new reference economic activities may emerge. For instance, the Guitang Group in China initially established its industrial symbiosis within the sugar production chain [11]. However, over time, additional economic activities, such as cellulose and paper production and combined heat and power units, which utilize organic waste from sugar production as part of the fuel source for heat generation, also became integral components of the network. Focusing on the methods of sharing resources, most of the case studies analysed are based on an exchange of by-products or waste (8 papers), of which 4 also share of infrastructure or services while 1 paper bases its IS network only on the sharing of infrastructure and services. Finally, the sharing of ancillary services is present in only one paper which applies all three exchange methods typical of industrial symbiosis.

The examination of case studies has emphasized how the success or failure of a synergistic relationship depends on multiple factors, rather than relying solely on the presence of a company capable of attracting others. It hinges on a combination of variables that exert a positive or negative influence. In particular, Table 2 illustrates the factors that impeded the symbiotic relationships in the 16 case studies that were analysed. In fact, the various economic, internal, external, structural, technical and social barriers are made explicit. One of the barriers that has been extensively discussed is geographical distance. However, the extent of this distance intrinsically depends on the profitability of the waste or by-product exchange. So far, the choice of partners' distance has been primarily cost-related, but it also hinges on the establishment of trust-based relationship, often referred to as "social proximity." This "social proximity" ensures that resources, upon which the production of other actors depends, are supplied within the pre-established timeframes and in sufficient quantities and quality to meet the agreed-upon needs. Another identified barrier is the imbalance between resource generation and consumption. In cases of surplus, when appropriately combined with the search for new connections, it can enhance the network's robustness and brings about economic, environmental, and social benefits.

Among the internal barriers encountered, one challenge was particularly common in most cases, which is the reluctance of companies to share data about their processes and waste generation. This reluctance, together with the lack of trust in the other entities involved in the network, hinders the expansion of the industrial symbiosis network. Tied to the concept of trust, and often foundational to it, is the assumption of moral and social integrity. This, in turn, is linked to the adequate training of the involved companies, which are often primarily focused on their own economic interests, potentially disregarding the multiple environmental and economic interests of other parties involved [25].

Table 2 Barriers

Economic barriers	- Processing, logistics, and administrative costs - Insufficient Funding - Cost of long-distance transportation
Internal barriers	- Risk of discontinuity in generation - Lack of research in finding new uses for surplus
External barriers	- Lack of Adequate Policies policies and regulations - Weak Regulatory Frameworks
Structural barriers	- Low number of symbiotic relationships (diversity issue) - Fragility causes limited functional and structural diversity
Technical barriers	- Imbalance between generation and consumption - High distance
Social barriers	- Prejudices related to product quality - Lack of partner training - Partners focused on their own interests - Lack of Openness and Willingness - Lack of trust

To address the lack of knowledge about companies that could potentially engage in symbiotic relationships, there is a solution in promoting the use of digital platforms and programs that facilitate connections between those seeking and offering waste and resources. Examples include online waste markets and e-marketplaces. These online platforms make it easier to establish synergistic relationships through more streamlined and effective communication among interested parties. The convenience and speed with which companies can share information regarding their waste and resource supply or demand, including details about material type, quantity, and geographical location, facilitate connections between interested parties. Additionally, they provide the flexibility in choosing partners based on economic considerations, such as pricing, distances, and potential environmental benefits. These tools not only support industrial symbiosis but also promote collaboration between companies that are not necessarily located near each other, thereby expanding the geographical scope of industrial symbiosis processes. Furthermore, these platforms facilitate social interaction between companies and the establishment of trust-based relationships, which have proven essential for the success of synergistic relationships, as evidenced by the analysis of the 16 case studies. It is evident from the case studies analysed that IS centres on the potential for collective growth among the various companies involved in the process. This approach aims to generate benefits for all participating members in different aspects, with a specific focus on sustainability, the promotion of the circular economy, and the development of ecological networks. However, it is important to note that each participant will receive a varying degree of benefits from this interaction. In other words, every entity can determine what to share and receive, whether it is the exchange of by-products or waste, the sharing of infrastructures or services, or ancillary services.

4 Conclusions

The analysis conducted in this paper has highlighted that industrial symbiosis has garnered significant attention from the academic world, national governments, and supranational institutions. These entities have recognized the importance of developing this innovative industrial process. The primary goal of this work was to examine industrial symbiosis, starting with the enabling context that has facilitated its adoption. It delved into various symbiosis models, discussing differences between them based on factors such as methods of formation (spontaneous or governed by a central authority), types of exchanges, and the level of implementation. Implementation levels may range from a single company with multiple production processes within it to two or more companies engaged in a synergy, exchanging at least one type of waste or by-product. These synergies can be located in proximity to each other or not. The study also explored the driving factors and obstacles influencing the implementation of industrial symbiosis. Recognizing the potential environmental, economic, and social benefits that can emerge from industrial symbiosis is crucial. Disseminating successful case studies and the key mechanisms that can facilitate or hinder

the establishment of synergistic relationships is vital for fostering new symbiotic relationships. This dissemination can inspire the emulation of existing partnerships and the application of various strategies to overcome barriers that have emerged in other contexts, serving as reference points. However, it is essential to acknowledge that this literature review has certain limitations. The analysis focused exclusively on publications in English, potentially missing out on valuable insights from publications in other languages. Additionally, relevant sources such as conference papers, industry reports, books, and book chapters were not included in the structured literature review. This deliberate focus on peer-reviewed academic journal articles was to ensure the quality of the publications reviewed.

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Assessing the Impact of Remanufacturing Through Industrial Symbiosis on Supply Chain Performance



Rebecca Fussone , Salvatore Cannella , Roberto Corsini ,
and Jose M. Framiñan

Abstract In the context of increasing resource scarcity, the Circular Economy has gained traction among researchers and managers as a potential solution to achieve a more sustainable system through efficient use of resources. Despite the importance of implementing circular practises in supply chains, the operational impact of circularity remains largely unexplored. Therefore, motivated by the existing interest in this topic, the aim of this work is to contribute to the current research gap and explore the impact of circularity on the dynamics of supply chains. Specifically, this study examines the performance of supply chains that incorporate remanufacturing through industrial symbiosis, i.e. which refers to the exchange of waste or by-products between different processes or firms, known as symbiotic supply chains. Using a modelling and simulation approach, this study evaluates the impact of operational factors on supply chain dynamics and identifies the most influential. Furthermore, this study offers practical guidance for managers seeking to integrate industrial symbiosis into their supply chains. Among our findings, we observe that, depending on the specific objectives of the supply chain, some circular strategies can have more impact on the dynamic performance of the supply chains than others.

Keywords Circular economy · Industrial symbiosis · Supply chain dynamics

R. Fussone (✉) · J. M. Framiñan
Industrial Management Research Group, University of Seville, Seville, Spain
e-mail: rfussone@us.es

R. Fussone · S. Cannella · R. Corsini
Department of Civil Engineering and Architecture, University of Catania, Catania, Italy

J. M. Framiñan
Laboratory of Engineering for Energy and Environmental Sustainability, University of Seville,
Seville, Spain

1 Introduction

In the current era of increasing resource scarcity, the Circular Economy (CE) concept has been advocated by researchers, policy makers, and business leaders [36] as it is increasingly recognised as a better alternative to the dominant linear economic model [19]. A CE is an economy that is restorative and regenerative by design, which aspires to a zero-waste system by circulating resources to minimise inefficiencies and by prolonging product life, recycling, remanufacturing, and reusing goods [6, 14]. The integration of CE in Supply Chain (SC) management has grown over the last decade, as SCs constitute a large segment of economic activities [1, 19]. To improve their operations and gain a competitive advantage, companies are interested in effective and efficient SC operations that, nowadays, need to embrace CE principles [30]. Thus the transition to a CE requires a transformation in SCs [6, 36].

In practise, integrating CE strategies into SC offers a new and compelling perspective for the SC sustainability domain [3, 13]. Indeed, while traditional Forward SCs (FSCs) involve flows of raw material and product from suppliers to final customers, in a CE, a SC should incorporate new complex flows of used products, by-products, and waste [24, 30]. Here, they are upcycled and reprocessed (through reusing, repairing, refurbishing, remanufacturing, and recycling) into a new useable form.

However, although in the SC dynamics literature there exist several works that study the Closed-loop SC (CLSC) configuration [9, 18, 20], that is, where end-of-life waste is reduced as used products are reinserted in the SC to be remanufactured, still few works analyse the SC configurations where waste and by-products produced in the production process are reduced, thus, where the Industrial Symbiosis (IS) is approached [10, 21, 28]. Indeed, according to Zhang et al. [36], “*SC researchers have not conducted much research on IS and the related open-loop circularity archetype*”.

IS plays a crucial role in the transition towards a CE by promoting resource efficiency, waste reduction, and cost savings, indeed, over the last years more and more scholars are studying its potential [15]. IS expands the traditional SC to include symbiotic suppliers and buyers, and resource or information sharing firms, i.e. creating Symbiotic SCs (SSCs) [29, 31]. With the emergence of research at the IS-SC management interface, there is an increased need to compare the IS oriented SCs, i.e. SSCs, with the traditional SCs [24, 29]. Although IS and SCs are intrinsically related, research in this area is scarce, and there are still several open questions on the dynamic behaviour of SSCs.

Specifically, the Bullwhip Effect (BWE), which refers to the amplification of orders along a SC [2], which worsen SC performance increasing inventory costs, decreasing customer service level, and logistics and transportation efficiency [23, 32, 34], is still quite unexplored in SSCs. Managing the BWE in SC is fundamental for companies aiming to build efficient and responsive SCs [32]. Indeed, it enables companies to identify inefficiencies, reducing costs, and enhancing customer satisfaction, as well as mitigating risks [22, 26]. In general, understanding and mitigating the BWE is a current challenge in traditional SC [27, 33].

Thus, merging the current need for SCs to go circular and the current challenge of traditional SC to manage the BWE, the aim of this work is to explore the behaviour and dynamic performance of SCs that include waste remanufacturing through IS. Specifically, we develop a modelling and simulation approach to study how the impact of symbiotic factors, i.e. waste rate and exchange period, impact on the dynamic performance of a SSC, focusing on bullwhip-related indicators. The structure of the paper is as follows. Section 2 describes the method and the modelling assumptions. Section 3 provides the experimental design and the selected evaluation metrics. Section 4 presents and discusses the results obtained and implications. Finally, Sect. 5 gives the conclusion and some future research directions.

2 Supply Chain Model

The SC model presented in this work consists of two three-echelon SCs, as depicted in Fig. 1. Here each SC actor satisfies the demand of its downstream actor on a make-to-stock basis. The methodological approach is discrete event simulation. Specifically, our model has been developed with Arena 16.2.

Between the three actors, one comes from the B2C (business-to-customer) world, i.e. the retailer, one from the B2B (business-to-business) world, i.e. the factory, and the third one deals with the raw materials supply, i.e. the supplier. Moreover, between the two factories, we assume a symbiotic exchange of waste. Specifically, on addressing its incoming demand, the factory of the second SC, which for the sake of simplicity we denote as *waste provider*, it generates and sends waste to the factory of the first SC, which we denote as *factory*. Once the waste is available, a *treatment remanufacturing process* is assumed to make it usable as input for the factory.

We base our model on well-established modelling assumptions from the SC dynamic and IS field [2, 8, 11, 16]. The ordering policy of each actor of the SC is the classical order-up-to (OUT) policy [7, 12], based on exponential smoothing demand forecast [4, 17, 20]. In other words, for each period, the SC actor i places an order $O^i(t)$ as follows:

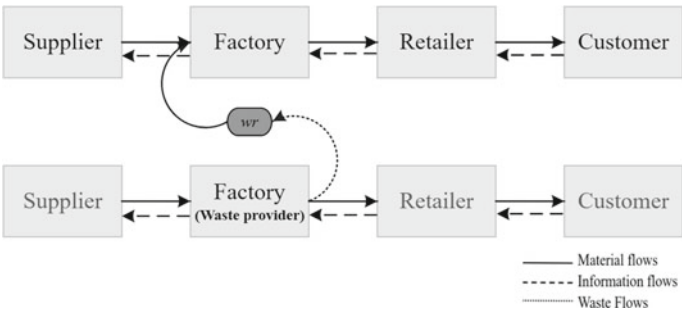


Fig. 1 Symbiotic supply chain schema

$$O^i(t) = \max \left\{ \hat{D}^i(t) + [SS^i(t) - NS^i(t)] + [TWIP^i(t) - WIP^i(t)]; 0 \right\} \quad (1)$$

Here $\hat{D}^i(t)$ is the forecasted demand, that is, as in Eq. (2), where α is the smoothing factor, $SS^i(t)$ is the safety stock, $NS^i(t)$ is the net stock, $TWIP^i(t)$ is the target work-in-process and $WIP^i(t)$ is the work-in-process.

$$\hat{D}^i(t) = \alpha \cdot D^i(t) + (1 - \alpha) \cdot \hat{D}^i(t - 1) \quad (2)$$

The sequence of actions that is performed by each SC member is as follows: (S1) it receives the previously ordered goods or material, (S2) it meets the actual demand, note that if the stock level is not sufficient, the demand is lost sale, (S3) it forecasts the incoming expected demand, and (S4) if necessary, it places an order to meet the OUT level. It should be noted that in S1 the factory also receives waste $W(t)$ from the waste provider, as indicated in Eq. (3).

$$W(t) = wr \cdot SD(t) \quad (3)$$

Here, SD is the satisfied incoming demand by the waste provider, and wr , which we denote as *waste rate*, represents the percentage of waste that can be remanufactured and then used by the factory. Once the waste is remanufactured, its quality is as the good as new material derived from the forward flow, as commonly assumed for remanufactured products in CLSCs [2, 20].

3 Experimental Approach

By analysing data from the configurations presented in the previous section, our aim is to provide insights into how to properly manage SSCs. To this end, we explore a wide range of scenarios through a planned experimental design, which is presented in this section.

As mentioned in the Sect. 1, IS mechanisms can include several types of exchange, such as materials, energy, by-products, heat, and so on. Depending on the nature of the waste, the shipping time and methods could be different. For instance, hazardous waste/materials should be used as soon as possible. On the contrary, there are other materials and by-products that can be stored before being remanufactured. For this reason, to simulate different real-life possibilities, we assume several scenarios in our analysis. We denote the time lag between two symbiotic exchanges as *exchange period* (EP), i.e. that is the time when the waste is stored before being sent to the factory. We simulate $EP \in \{1, 7, 14, 30\}$ (i.e., to simulate daily, weekly, biweekly, and monthly symbiotic exchange). It should be noted that $EP = 1$ means that there is an exchange at each time unit, which can be associated with hazardous waste

or waste with short usage, such as those from the agri-food industry. While waste characterised by larger EP can be stored and they are not subject to rapid detriment.

The parameters that have been set as fixed are: lead time $LT = 4$, waste treatment remanufacturing lead time $WLT = 2$ and $\alpha = 0.1$. While we explore 10 values for the waste rate, $wr \in \{0; 0.1; 0.2; 0.3; 0.4; 0.5; 0.6; 0.7; 0.8; 0.9\}$ to understand how this key factor in SSCs affects their performance, i.e. as the waste rate informs us about the volume of exchanged waste. Note that $wr = 0$ represents the traditional FSC that is set as a benchmark. We assume that both SCs are subject to the same customer demand that follows a normal distribution, i.e., $D = N(100,30^2)$.

The combination of the selected parameters results in 40 scenarios to explore. Each scenario has been investigated through 20 simulation runs (i.e. replications) for a length of 2500 periods, where the first 200 periods have been removed as a warm-up horizon.

3.1 Performance Measurement

The selected Key Performance Indicators (*KPIs*) are shown in Table 1. The *Order Variance Ratio* (*OVr*) is the most common demand amplification measure in the literature [11]. This compares the variance of orders to that of customer demand. A value larger than one indicates that the BWE is present, i.e. there is order amplification along the SC. This metric is indicative of production efficiency, as it is related to variable capacity-related production costs [5]. However, by definition the bullwhip-related metric includes the mean of the orders and of the demand, i.e. in the *Order rate Variance Ratio* (*OrVrR*) variances are reported to their respective mean values, which, as in the CLSCs (see [12]), in the SSC are expected to be different. We will also evaluate the *Inventory Variance Ratio* (*InvVrR*) to measure net stock instability. When SCs are appropriately controlled, minimising *InvVrR* results in a reduction of the sum of holding and backlog costs [11]. Finally, the *J-index* is an order-inventory variability trade-off metric, defined as the weighted average of the square roots of *OrVrR* and *InvVrR*, where k_o and k_i indicate the weight of both terms and inform on the unit costs of over-ordering, underordering, storage, and stock-outs [4, 25].

Table 1 Bullwhip-related KPIs

Name	Formula	Name	Formula
Order variance ratio	$ORV = \frac{\sigma_o^2}{\sigma_D^2}$	Inventory rate variance ratio	$InvVrR = InvVrR = \frac{\sigma_i^2/\mu_i}{\sigma_D^2/\mu_D}$
Order rate variance ratio	$OrVrR = \frac{\sigma_o^2/\mu_o}{\sigma_D^2/\mu_D}$	J-index	$J = k_o \cdot \sqrt{OrVrR} + k_i \cdot \sqrt{InvVrR}$

4 Results and Discussions

This work deals with the exploration of evaluating performance indicators in a SSC configuration. In this section, the numerical results of the simulation study will be analysed and discussed. Then, we provide an overview of the main results and discuss their relevance to those who intend to continue investigating SSCs and their modelling, as well as to managers that want to implement IS.

Starting from the order variability indicator, as shown in Fig. 2, it can be seen that the trends of the *OVR* indicator and the *OrVrR* indicator are opposite when $EP = 1$. Indeed, for the *OVR*, as wr increases, the indicator decreases. In fact, for each wr , the factory reveals less *OVR* compared to the $wr = 0$ scenario, which is the traditional FSC scenario. This means that when the variability of the waste volume increases, the factory order variability decreases. However, the *OrVrR* increases with the wr , which was expected due to the decrease of the order average, by definition, for the symbiotic scenario, i.e. $\mu_{O_i} = (1 - wr) \cdot \mu_D$. It suggests that the *OVR* decrease does not imply an improvement in the order fluctuation. Indeed, while the variance decreases, the variance ratio, i.e., *OrVrR*, increases with wr .

Moving to the $EP > 1$ impact on the order related indicators, the implications and variable interactions are different compared to $EP = 1$. Although for both *OVR* and *OrVrR* when $EP = 7, 14$ and 30 their values and trends differ slightly between each other, for the *OrVrR* we observe a rapid increase in their values compared to the $EP = 1$ scenario. Here, indeed, when wr increases, both the *OrVrR* and the distance between the $EP = 1$ scenario and the $EP > 1$ scenarios increases.

Concerning the *OrVrR*, it always increases with wr . While moving to the *OVR* for $EP = 7, 14$ and 30 , here its values are always higher compared to the FSC scenario, i.e. $wr = 0$. However, we observe an increase with wr up to $wr = 0.4$, then its values start to decrease.

Concerning the *InvVrR*, shown in Fig. 3, we note how the variance of the inventory is affected by the arrival of waste from the waste provider. However, this indicator is more affected than the order-related ones by the EP . Indeed, it increases with EP and the largest increase is observed for high values of wr . From a value of 80% of waste sent from the waste provider, i.e. $wr = 0.5$, we see an increase of almost 50% in this indicator for each step of the EP increase. Noting that during EP waste is

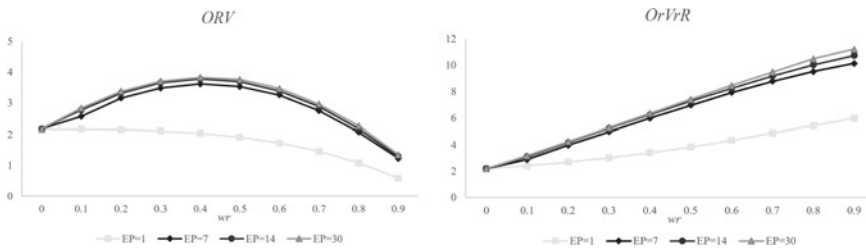


Fig. 2 Interactions of wr and EP for *OVR* and *OrVrR*

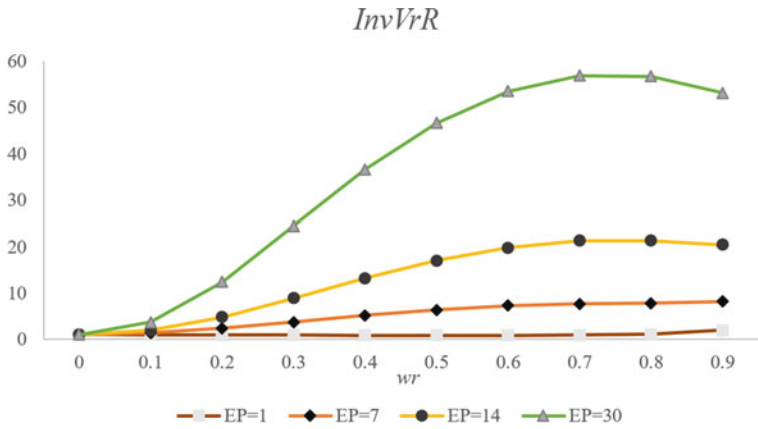


Fig. 3 Interactions of wr and EP for the $InvVrR$

stored and at the end of EP the factory will receive a larger volume of waste that will drastically increase its inventory level when wr is high. This results in lower orders for the following time units.

Analysing the results mentioned above, it should be noted that it arises that the SSCs are more sensitive to inventory amplifications; indeed, although for high wr and longer EP the factory receives a large volume of waste all at once, the order variability is less affected than the inventory one, which instead results in poor performance. For this reason, we also include the J -index metric, i.e. as shown in Fig. 4. Indeed, depending on the cost structure of the firm, i.e. if ordering costs are higher than inventory one or vice versa, the performance of a SC that wants to implement the IS can behave in different manners.

It should be noted that if a firm is involved in the symbiotic exchange and its inventory costs are higher than the ordering one, i.e. $k_i > k_o$, that in our study is $k_o = 0.25$ and $k_i = 0.75$ (see Fig. 4), it should favour shorter EP to minimize the J-index. On the other hand, if it is not possible due to the contract that establishes the IS, they should try to minimise the cost for the inventory, even if at the expense of a higher cost for the orders.

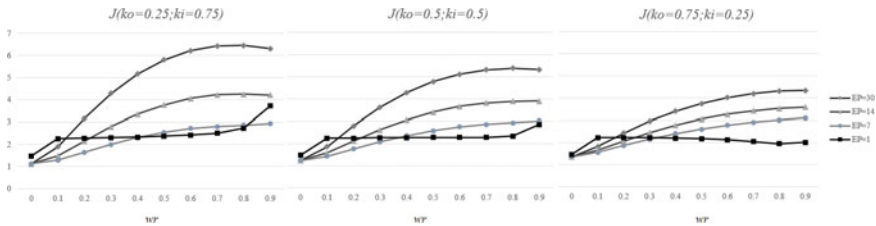


Fig. 4 J-index trends for different w and EP

4.1 Implications and Insights

Assuming that implementing a SSC is beneficial in terms of economic benefits for the waste provider as it reduces its waste disposal costs, as well as it increases its profit by selling these waste to the firm that receives waste. For the SC actor that remanufactures waste itself, the real economic benefit is gained when the price of the waste is lower than the price of raw materials. Noting that the *BWE* also provides information related to operational costs, it is important to take it into account, both for the economic and SC dynamics perspective.

Our results reveal that the *BWE* is not always minimised in implementing IS, thus, it should be accurately managed to gain real benefits in remanufacturing waste. Indeed, our results show that not all SSC configurations provide improvements in dynamic performance. If not well managed with tuned inventory and replenishment policies, both for the forward flow and for the symbiotic flow, the previously mentioned economic improvements can be harmed, i.e. lower input costs at the expense of higher bullwhip related costs and damaged dynamic performance.

However, it is worth mentioning that this work is based on specific modelling assumptions. For example, in implementing IS according to our modelling assumptions, a $wr = 1$ indicates that 100% of the waste is sent from the waste consumer and this will obviously lead to greater availability of products, but also to a lower variability of the orders as well as reduced order magnitude. However, if the two involved SCs are subject to different final customer demand, this implication may differ. For example, if the SC of the waste provider is subject to a bigger final customer demand than the SC that receives the waste, a significant volume of waste will already be shared for small waste rates. On the contrary, if it is plenty smaller, high waste rates will may not allow the factory to be fully replenished by the waste.

5 Conclusions

The transition to the CE paradigm poses a significant challenge for companies to go towards a more sustainable and efficient economy. A possible way to adopt CE principles is to implement IS, which has been widely recognised as a promising strategy for achieving sustainable development. Interestingly, while IS has been extensively studied in the context of sustainability, it has received little attention in the field of SCs and its impact on SC operational performance remains largely unexplored. Therefore, the objective of this study is to explore the dynamics of SSCs. We analyse several symbiotic scenarios with different exchange periods for waste and different waste rates. Specifically, this study revealed that the implementation of a SSC does not always minimise *BWE*, necessitating careful management to achieve real benefits in waste remanufacturing. Certain SSC configurations do not improve dynamic performance unless inventory and replenishment policies are fine-tuned for both forward and symbiotic flows. However, it should be noted that this research is

based on specific assumptions and modelling frameworks that may not fully capture the complexities and variations of real-world SSCs. Generalising the findings to different industries or contexts should be done with caution. Our study focusses primarily on assessing the BWE in a SSC and the impact on waste remanufacturing. Other factors such as environmental impacts, social aspects, and overall resilience of SC have not extensively explored. Future research could explore the implications of different customer demands on waste exchange scenarios within the SSC. In addition, the role of information sharing, collaboration, and coordination among different actors in SSCs can be investigated. Finally, future studies can analyse the resilience of SSCs to disruptions, such as changes in customer demand or regulatory shifts and explore risk management strategies to ensure continuous waste flows within SSCs.

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Manufacture of a New Sustainable Material from Bacterial Cellulose from Organic Waste in a Circular Economy Framework



Cristina Moreno-Díaz , Piera Maresca , Marcello Fera ,
and Salvador González-Arranz

Abstract The circular economy introduces a novel approach to sustainable production and consumption, emphasizing collaboration to develop innovative business models. Material innovation is a key element in aligning with this circular economy, transcending traditional disciplinary boundaries. This article focuses on bacterial cellulose, a material naturally produced by bacteria. Due to its mechanical strength and eco-friendly qualities, it offers a sustainable alternative to plastic materials. We start with a theoretical-technical overview and then explore practical Do It Yourself (DIY) applications. Our emphasis is on producing bacterial cellulose from local organic waste, in line with circular economy principles. We conduct a field study to assess local producers' readiness to contribute organic waste for bacterial cellulose production. The waste collected is used to create practical, disposable, and compostable solutions, which are returned to local stakeholders, closing the production and consumption loop. These solutions also serve as raw materials for further cellulose synthesis. In summary, this article investigates bacterial cellulose as a sustainable material and implements a circular economy approach by utilizing local organic waste for material production and reuse. This contributes to a more sustainable, closed-loop system, fostering innovation and collaboration.

Keywords Circular economy · Sustainable materials · Zero manufacturing waste

C. Moreno-Díaz (✉) · P. Maresca · S. González-Arranz
Universidad Politécnica de Madrid, Madrid, Spain
e-mail: cristina.mdiaz@upm.es

M. Fera
Università Degli Studi Della Campania Luigi Vanvitelli, Caserta, CE, Italy

1 Introduction: Circular Economy and Materials Design

The linear production and consumption system has irreversible consequences on ecosystems. While this linear model results in decentralized production and urban waste management challenges [1], the circular economy strives to promote material reuse and minimize waste. To achieve sustainability, it is imperative for cities to innovate and develop collaborative solutions, becoming more self-sufficient [2].

Throughout history, human progress has often relied on the utilization of previously discovered materials to drive technological advancements. However, it is crucial to recognize the pivotal role of material innovation in this process. Materials transcend disciplinary boundaries and serve as catalysts that unite diverse stakeholders in the pursuit of sustainability. Designers, scientists, and entrepreneurs engage in the exploration of novel material combinations and their innovative potential, sharing ideas and knowledge through multidisciplinary collaboration.

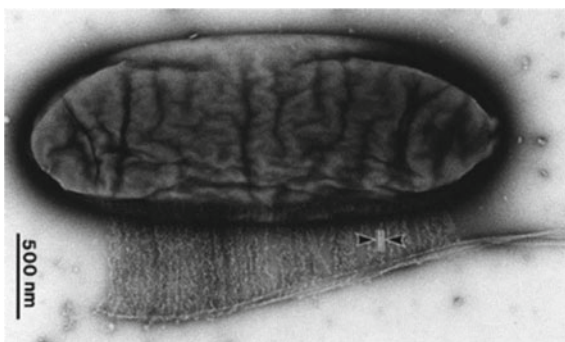
In this context, nature emerges as a wellspring of inspiration for sustaining life on our planet. Biomimicry encourages humans to adapt to Earth through bio-inspired and bio-emulated models [3]. Designers find valuable partners in nature, exploring material combinations and their innovative capabilities. Biodesign seeks to integrate living organisms into manufacturing processes, tools, and products, with the ultimate aim of achieving sustainable production systems. Collaboration with disciplines such as biology drives the quest for alternative material solutions. Material designers take on the role of “cultivators,” creating optimal conditions for microorganisms to thrive and acquire desired characteristics [4]. In our project, we have focused on bacteria that produce bacterial cellulose, an exemplary material for fostering a more sustainable circular production system. This paves the way for scaling such projects at urban and industrial levels.

This study aims to explore the integration of bacterial cellulose into the context of the circular economy, particularly in the context of remanufacturing. We seek to highlight the specific objectives of our research in demonstrating how bacterial cellulose can be a key component in sustainable circular production systems and how it aligns with the concept of remanufacturing.

2 Bacterial Cellulose

Bacterial cellulose (BC) is a polysaccharide biopolymer composed of glucose that is naturally synthesized by certain bacteria [5], such as bacteria from the *Komagataeibacter* genus, which is the most advanced among them [6] (see Fig. 1). In this regard, *Komagataeibacter* bacteria are commercially used for vinegar fermentation or for producing highly acidic beer [7]. Furthermore, these bacteria naturally inhabit organic matter with high sugar content, such as decomposing fruits and vegetables, from which they can be isolated.

Fig. 1 *Komagataeibacter xylinus* bacteria producing a cellulose microfibril [8]



Cellulose is considered the most abundant renewable biopolymer on Earth and holds tremendous economic significance worldwide [9]. In particular, BC has gained increasing interest in recent years (see Fig. 2) due to its highly attractive properties for a multitude of applications.

From a structural perspective, cellulose, regardless of its source, consists of a polymer of glucose residues linked by covalent bonds between carbon 1 and 4 (β 1-4), forming a linear chain. These linear polymer chains associate, leading to the formation of cellulose microfibrils (see Fig. 3) [5]. These microfibrils, in turn, crystallize into bundles and ribbons, forming an extensive cross-linked structure stabilized by hydrogen bonds (see Fig. 4). The condensation of ribbons results in the three-dimensional structure or macrostructure of BC [10].

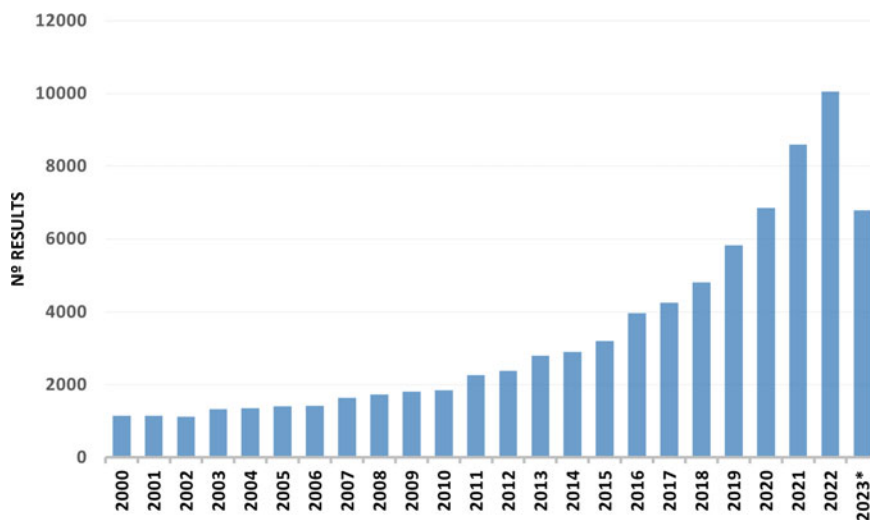


Fig. 2 Number of search results on Science Direct for the search term “Bacterial Cellulose” per year [10]. Compiled by the author

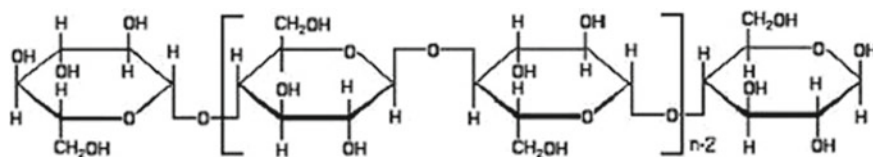


Fig. 3 Molecular structure of bacterial cellulose [5]

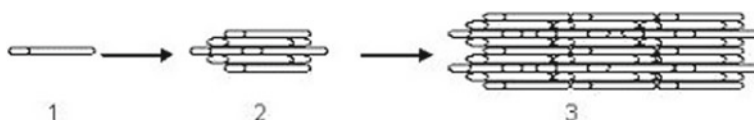


Fig. 4 Microstructures of bacterial cellulose. 1. Linear chain of BC. 2. BC microfibril. 3. Macrostructure of BC. [5]

The properties of BC are of great interest due to its various potential applications. Table 1 summarizes these mechanical properties and compares them with other organic materials. Studies conducted on BC have shown elastic modulus values, E , ranging from 16 to 18 GPa, as well as a tensile strength, σ_{lim} , of 250 MPa. Furthermore, it has been observed that these properties can be enhanced through post-cultivation treatments such as cleaning with sodium hydroxide, which helps remove impurities from the cellulose network and improve the interaction between nanofibers [11].

In addition to its mechanical properties, among all its characteristics:

- High degree of crystallinity
- Higher surface area compared to conventional wood pulp
- Sheet density 300–900 kg·m⁻³
- High tensile strength
- High absorbency
- High elasticity and durability
- Non-toxic
- Metabolic inactivity
- Biocompatibility
- Susceptible to degradation
- Great shape retention

Table 1 Mechanical properties of bacterial cellulose and other organic materials [12]

Material	E (GPa)	σ_{lim} (MPa)	Elongation (%)
Bacterial Cellulose	15–35	200–300	1.5–2.0
Polypropylene (PP)	1–1.5	30–40	100–600
Polyethylene Terephthalate (PET)	3–4	50–70	50–300
Cellophane	2–3	20–100	15–40

BC stands out for its biocompatibility and hydrophilicity. Furthermore, being biodegradable and compostable [10], it carries an “eco-friendly” label, allowing it to compete with some well-known plastic materials. All these features make it a material with great potential for application in various sectors such as medicine, food industry, packaging, textile industry, and technology (Table 2).

The production of BC involves growing bacteria in a carbon- and nitrogen-rich culture medium in optimal conditions. One of the most used culture media is the Hestrin-Schramm (H-S) medium (Table 3), using *Komagataeibacter xylinus* bacteria [20].

The key cultivation parameters for BC production include the cultivation method, carbon and nitrogen sources, pH, and temperature of the culture medium. Optimal pH values have been observed to range between 4.5 and 7.5, with the highest efficiency around pH 5 [21]. Furthermore, the optimal temperature for BC production has been determined to be 28 °C [22].

Efficient production of BC by these bacteria relies on their ability to synthesize glucose from the carbon substrate and polymerize it into cellulose. To maximize production, different carbon sources such as mono- and oligosaccharides, alcohols, and acids have been tested [23]. In particular, the use of complex carbon sources such as hydrolyzed molasses or beet molasses [24] has been found to increase cellulose

Table 2 Industrial applications summary of bacterial cellulose [13–19]:

Industry	Applications
Cosmetics	Stabilization of emulsions, conditioners, creams, and production of artificial nails
Textile	High water absorption material and substitute for animal leather in textile applications
Refinery	Absorbent material for toxins and oils in environmental cleanup
Paper	Restoration of documents and production of high-quality paper
Food	Food additive, emulsifier, and dietary fiber in food products
Tourism	Use in sportswear and camping gear
Research	Immobilization of proteins and cells, chromatography resins in laboratory settings
Technology	Application in high-sensitivity diaphragms for microphones and hearing aids
Medicine	Manufacturing of “artificial skin” for burn therapy and wound healing
Biomedical	Scaffold material for tissue engineering and regenerative medicine applications

Table 3 Hestrin-Schramm (H-S) medium for *Komagataeibacter xylinus* [20]

Component	Amount	Component	Amount
Glucose	20 g	NaH ₂ PO ₄	2.7 g
Peptone	5 g	Citric acid	1.15 g
Yeast extract	5 g	Distilled water	1000 ml

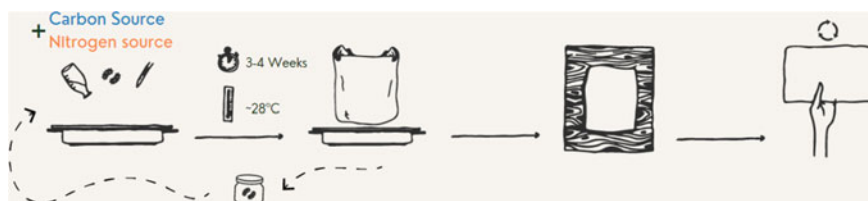


Fig. 5 Common cultivation procedure of bacterial cellulose

production compared to using glucose as the sole carbon source. This is due to the presence of additional micronutrients in molasses, especially sulfurs and organic nitrogen, which promote microbial growth. Currently, research is being conducted on the use of other types of complex carbon sources obtained from byproducts or waste in various distillations and fermentations in the agricultural industry [13].

The process of BC formation occurs layer by layer, like additive manufacturing. Additionally, BC can adapt and take the shape of any surface in the cultivation vessel. The bacteria reproduce in this carbon- and nitrogen-rich aqueous medium, from which they obtain nutrients and excrete cellulose that accumulates to form a layer on the liquid surface. The common and well-known procedure for BC production (Fig. 5) generally involves extracting the cellulose layer after approximately three to four weeks and reintroducing it along with the culture liquid in the production cycle as a carrier material for bacteria. Alternatively, the cellulose layer can be treated and dried to obtain the final dehydrated material, which is also fully compostable [25].

3 Production, Integration, and Applications

3.1 *DIY Production of Bacterial Cellulose*

As mentioned above, BC can also be produced in a domestic and accessible environment. In this context, this material is also known as “bacterial leather,” “kombucha leather,” “SCOBY” (Symbiotic Colony of Bacteria and Yeast¹), or “vegan leather”. BC is traditionally created as a film formed on the surface of fermented kombucha tea,² which contains the necessary nutrients, bacteria, and yeast to produce BC. This process involves adding bacteria to a culture medium based on sugar, tea, and sometimes vinegar (replacing the components presented earlier that constituted the H–S culture medium, mainly used at the scientific level, see Fig. 6).

¹ Although the definition of this term refers to the entire set of bacteria that produce CB, in this context, SCOBY is known solely as the cellulose film itself, which serves as the “mother” for cultivating new CB. Therefore, from now on, the word SCOBY will refer to the cellulose film.

² It is a probiotic tea fermentation beverage originating from China, Russia, and Germany, and consumed worldwide [26].



Fig. 6 Different culture media: H-S and DIY

A simplified schematic of bacterial cellulose production appears in Fig. 7, and shows the steps to follow considering the reuse of the medium on which the BC layer grows and Fig. 8 illustrates the experimental production process followed in the laboratory.

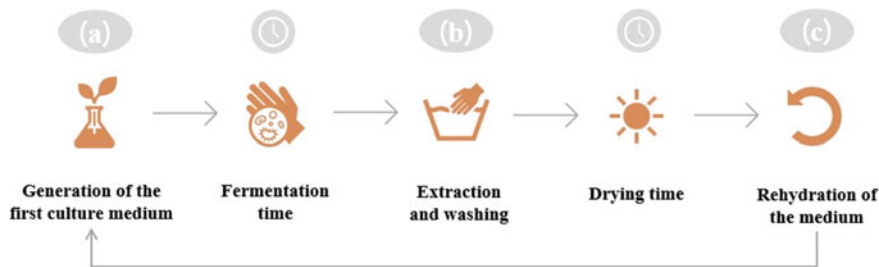


Fig. 7 Simplified schematic of bacterial cellulose production with reuse of medium

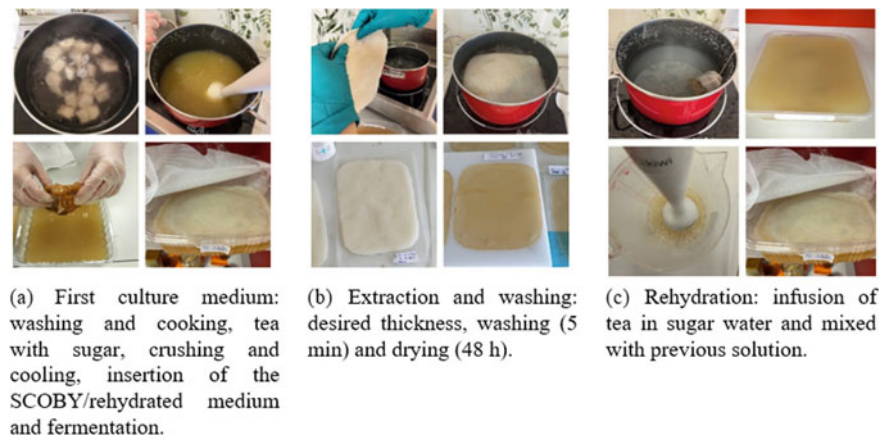


Fig. 8 Steps followed in this work to produce the experimental BC

The films are formed after a couple of weeks (the longer the time, the thicker the film). The techniques are simple, and there are infinite possible alterations to investigate parameters such as color, texture, thickness, or anything one wishes to invent. These DIY techniques create the opportunity for anyone to produce their own BC film in a completely domestic and accessible way, with applications ranging from thin and translucent wrapping films to thick textiles with a variety of properties [26].

There are many projects that utilize these DIY techniques to obtain material samples and experiment with different manufacturing and application methods. Furthermore, linking to one of the latest advances described in the previous section, it is even possible to replace the necessary sugar with food waste rich in sugars, as demonstrated by Ellen Rykkeliid in her experiments [27] (see Fig. 9). This approach yields excellent growth results, often better than using table sugar. These organic leftovers (preferably from fruits and vegetables) can range from potato peels, ripe tomatoes, carrots, blueberries, or beets to grass or leaves. Not only are they a great source of cheap production that would fit perfectly within a circular economy of local production, but their utilization could also provide special surface properties to BC through the application of natural dyes or different textures.



Fig. 9 CB cultivation based on fruit leftovers by Ellen Rykkeliid [27]

3.2 Integration into the Local Production Environment and Closing of the Production Cycle

Taking advantage of the accessibility of these DIY techniques and the shared Open-Source information among designers, creators, and biologists, this project investigates the possibility of using BC production as a tool to generate a circular economy based on the reuse of locally generated organic waste.

Therefore, with the aim of putting into practice an example of circular production, the experiments carried out in this project extended towards a systematic production concept that was based on the local environment and resources of the Lavapiés neighborhood in Madrid, Spain. This research explores the integration of a possible BC manufacturing into the current production system through visits to local basic food producers (see Fig. 10).

A field study was conducted through surveys and on-site visits, which served, firstly, to map the surplus organic matter that could be used to produce the material, locating these surpluses in fruit shops, restaurants, and cafes. Secondly, to identify the disposable product needs of these businesses. And ultimately, to build collaborative relationships with these raw material distributors. All the above has allowed for the collection of these useful organic residues for BC production.

Simultaneously, different samples of BC have been effectively produced using organic waste products, totaling 2 m² distributed among 35 samples, Fig. 11. Various culture media were experimented. Production was even tested using alcoholic beverages, which expands the range of possibilities for the utilization of other types of waste from different sources. The production results in samples that vary in flexibility, rigidity, texture, thickness, or color. These attributes are conditioned by controllable parameters such as the raw material used, cultivation conditions, or the washing and drying process after the extraction of the cellulose sheet.



Fig. 10 Map of local stakeholders of interest for the project in the Lavapiés neighborhood (Madrid, Spain) and collected waste products from local stakeholders of interest



Fig. 11 Several obtained samples

Different materials have been successfully synthesized, exhibiting several behavior and appearance (Fig. 12).

Various manufacturing methods have been tested, such as 3D printing with crushed BC, extrusion, laser engraving and cutting, or coloring. All of this envisions the adaptation and application in different fields, including single-use packaging, writing paper, textiles and clothing, or furniture design, among others.



Fig. 12 From upper left to down right: Beer waste with a texture like leather. Banana waste with a texture like vegetable parchment paper. Mix of fruits and vegetables with a texture like rough cardboard or paper. Sample made from banana waste with a texture like plastic material

3.3 Applications with Bacterial Cellulose

During conversations with businesses in the field study, certain needs for disposable products were identified, which present an opportunity for the application of BC. Specifically, two prototypes are shown. Firstly, a product intended for fruit shops or wholesalers, consisting of a cover sheet for boxes, Fig. 13. This product has a dual functionality, as it can be transformed into a cone through origami, taking advantage of its flexibility and fold resistance. The cone can be used as a container or packaging in markets, in the store itself, or as a promotional gift in home deliveries, emphasizing both advertising intentions and customer connection (see Fig. 14).



Fig. 13 Fruit box cover prototype

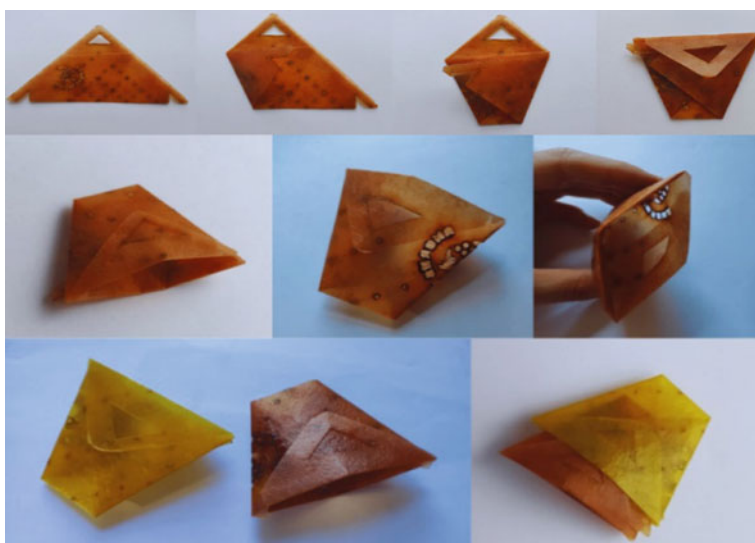


Fig. 14 Images of prototype 1 origami process and transformation into a cone



Fig. 15 Prototype 2: tray liner (left) and highlighted detail (right)

Secondly, another element has been prototyped for different types of businesses such as canteens, cafeterias, or restaurants. It consists of a sheet that serves as a tray liner and also incorporates the logo of the business and the raw material used, Figure 15 this element also allows for the evaluation of laser cutting as a manufacturing method with BC, to analyze the possibilities of producing final elements with this material.

These prototypes serve to showcase the enormous potential for industrialization in numerous applications of BC. This hybrid material, which can be both food-grade and non-food-grade, could lead to new applications in industries related (or unrelated) to food, such as packaging, which are currently dominated mainly by disposable (non-edible) products that end up in landfills or are recycled into lower-quality materials.

4 Conclusions: Scalability and Industrialization Possibilities

This project takes a DIY approach but aims to pave the way for scalable and industrialized processes, leveraging the creative and research ecosystem where similar local projects are emerging. By producing BC from organic waste, it aligns with the cradle-to-cradle philosophy. Various profitable fermentation methods have been identified for BC production using industrial organic waste, such as brandy, fruit juices, maple syrup, wheat straw, and more, with high production yields observed in many cases.

The transformation of food waste into BC presents a significant opportunity within the food production system. It can be implemented circularly in closed regenerative cycles, benefiting local production systems. Collaboration among various local entities, including residents, businesses, cultural centers, and universities, is crucial in achieving this vision and integrating collaborative projects into cities. This approach also centralizes production and consumption activities within cities, fostering self-sufficiency at the neighborhood level.

Moreover, there are promising business opportunities associated with BC. Environmentally conscious companies and those generating large quantities of food byproducts could be interested in utilizing it. BC can be used in both B2B and

B2C dynamics, enabling applications such as street food stalls manufacturing take-away containers from food waste or cafes using coffee grounds to produce disposable items while also serving beverages. Supplying materials to third parties and collaborating with companies in the agricultural sector can further expand production volumes. However, this approach is not without challenges. The collection and effective management of these organic waste materials on a large scale, the standardization of bacterial cellulose production processes, and quality assurance are hurdles that need to be addressed. Furthermore, education and collaboration with local stakeholders are essential to ensure acceptance and participation in this circular approach. Ultimately, this practice relates to remanufacturing by closing the loop of production and consumption since the practical and compostable solutions created from bacterial cellulose can be reused and remanufactured into new products, thus contributing to a more circular and sustainable economy.

The potential of BC in various applications, combined with its circular sourcing from food waste, attracts attention from different sectors and professionals, fostering cross-disciplinary innovation.

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Circular Economy and Autonomous Remanufacturing for End-of-Life Offshore Wind Turbines



Mahmood Shafiee

Abstract Offshore wind energy is considered as one of the fastest growing sustainable energy sources in the world. Offshore wind turbines (OWTs) are the most common technology used to harness wind power at sea for conversion to electrical energy. OWTs are often designed for a lifespan of 25 to 30 years, with a possible extension of up to 5 years. Most of the OWTs that were installed in the 1990s and early 2000s have reached, or are approaching, the end of their service lives. This has resulted in increasing concerns about how the large quantities of materials extracted from end-of-life OWTs can be best utilized. “Circular economy” is a new area of research that has recently attracted considerable interest from the offshore wind energy community. This paper aims to present an analysis of the technological, economic, environmental, regulatory, policymaking, cultural, and social challenges confronting the offshore wind energy industry with respect to end-of-life management, including reusing, retrofitting, recycling, remanufacturing, and repowering of OWTs, to support the transition toward circular economy. We then outline some of the business opportunities that Industry 4.0/5.0 and digital technologies can provide for building a more circular and sustainable wind power industry in the future.

Keywords Circular economy · Offshore wind energy · Autonomous remanufacturing · Industry 4.0/5.0 · Digital technologies

1 Introduction

Offshore wind energy is considered as one of the fastest growing sustainable energy sources in the world. According to the Global Wind Energy Council (GWEC), the total installed capacity of offshore wind energy worldwide reached about 64.3 gigawatts (GW) by the end of 2022 [1]. Of all the regions in the world, Europe is the leader in offshore wind energy, with nearly 30 GWs of installed capacity in 2022 [2]. The EU has set an ambitious target of 60 GW of offshore wind power capacity

M. Shafiee (✉)

School of Mechanical Engineering Sciences, University of Surrey, Guildford GU2 7XH, UK
e-mail: m.shafiee@surrey.ac.uk

by 2030. Offshore wind turbines (OWTs) are the most common technology used to harness wind power at sea for conversion to electrical energy. OWTs are often designed for a lifespan of 25 to 30 years, with a possible extension of up to 5 years [3]. Most of the OWTs that were installed in the 1990s and early 2000s have reached or are approaching the end of their service lives, and therefore they are likely to be shut down in the coming years. “Decommissioning” is the last phase of the life cycle of any offshore wind project. This phase consists of all activities carried out before, during, and after dismantling of OWTs and their supporting infrastructure, including foundation structures, transmission cables and electric units, and onshore and offshore substations. OWTs are disconnected from the grid, the components are dismantled, items left-in-place are buried or marked, and eventually the site is returned to, or as close as possible to, its original state [4].

The volume of decommissioning activities in the wind energy industry is expected to rise significantly over the next five to ten years. About 454 MW of Europe’s wind power capacity was decommissioned in 2022, with another 1.5 GW of capacity that was ready for decommissioning, but the wind turbines continued to operate as the electricity prices went up [2]. With the growth in the number of OWTs to be decommissioned, significant volumes of waste materials including steel, copper wire, electronics and gearing are expected to be generated. This has raised increasing concerns in the international community about how to best utilize the materials extracted from end-of-life OWTs. Presently, the waste generated from OWTs is treated in three ways: (i) recycling; (ii) landfilling, and (iii) incineration or combustion. More than 80 percent of the mass of wind turbines is made up of materials that are recyclable, such as steel, cement, copper, and iron [5]. However, the remaining materials such as glass fiber, epoxy resin, polyester resin, and acetone are challenging to be recovered, and as such, must be sent to a landfill site or incinerator. For instance, wind turbine blades are made from fibre-reinforced composites which are currently difficult to recycle due to the complex composition of numerous materials that are tricky to separate [6].

“Circular economy” is an emerging research area that has been attracting a lot of attention from the offshore wind industry in recent years. A circular economy is an economic system that aims to eliminate or minimize waste from production to consumption through the continual use of existing resources. This system relies on three key principles: designing out waste and pollution from processes and products; keeping products and materials in use by prolonging their lifespan; and regenerating natural resources. The circular economy employs methods of reuse, repair, refurbishment, remanufacturing, and recycling to create a closed-loop system that uses less resources and produces less waste, pollution, and carbon emissions. The success of a circular economy relies on many technological, economic, regulatory, environmental, political, cultural, and social dimensions. This paper presents a detailed analysis of the challenges confronting the offshore wind energy industry with respect to end-of-life management of OWTs, with the aim of supporting the transition toward circular economy. Moreover, we outline some of the business opportunities that Industry 4.0/5.0 and digital technologies can provide to enable the wind power industry to become more sustainable and circular in the future.

The rest of this paper is structured as follows. Section 2 reviews the research studies published in the field of circular economy and end-of-life waste management within the wind energy industry. Section 3 discusses the barriers that the offshore wind industry faces in adopting circular economy principles and practices. Section 4 outlines some of the areas of technology that Industry 4.0/5.0 has to offer. Finally, the paper is concluded in Sect. 5.

2 Literature Review

Circular economy is a new concept that is gaining popularity in the business world and being applied in a wide range of industries. The wind energy industry is committed to accelerating the transition to a circular economy by achieving full recyclability of wind turbines and other components [7]. A report by the Offshore Renewable Energy Catapult estimates that a circular economy transition in the wind energy sector could reduce carbon emissions by 34% and create 20,000 additional jobs in the UK [8]. Despite this, there has been very little research concerning circular economy in the wind energy sector. Achieving circularity is a complex and multi-faceted challenge, requiring the concerted efforts of governments, businesses, and academics. In a research article [9], a whole system approach was proposed on how to implement circular economy principles in offshore wind farms, involving a wide range of activities from design for circularity to extending component lifetime with improved repair and maintenance, reusing and refurbishment, remanufacturing, recycling, energy recovery, and disposal. In another research article [10], a framework was proposed on how to embed circular economy principles into the lifecycle of OWTs, including different end-of-life strategies such as repowering, lifetime extension, reusing and repurposing, refurbishment, and remanufacturing, as well as recycling and energy recovery. These end-of-life strategies for wind turbines are shown in Fig. 1.

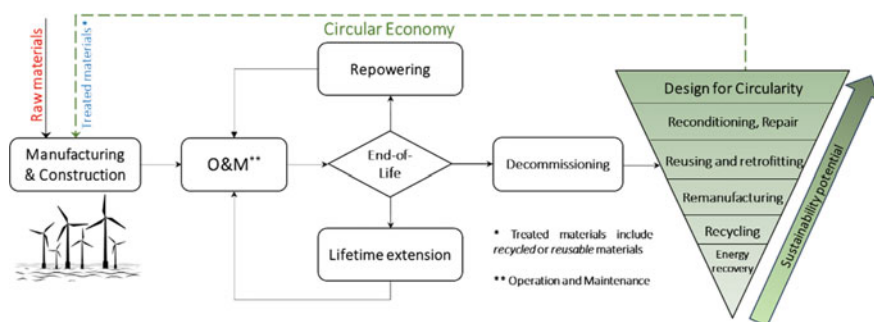


Fig. 1 The end-of-life options for wind turbines

Mendoza et al. [11] identified different circular business models applied to the wind energy sector and evaluated them based on (i) business offering and drivers, (ii) value creation, delivery, and capture mechanisms, (iii) sustainability benefits and trade-offs, and (iv) industrial challenges and opportunities. Woo et al. [12] identified several key technical, economic, and regulatory issues that must be addressed before deciding on the most appropriate end-of-life option for OWTs. The research concluded that designing for circularity, stakeholder collaboration, circular business models and technology-specific regulations can improve the end-of-life sustainability. Vielen-Kallio et al. [13] reviewed the current state of knowledge and identified research gaps in circular economy research for wind turbines. Gennitsaris et al. [14] presented a life cycle analysis (LCA) and data envelopment analysis (DEA) approach, integrating all technological, economical, and environmental aspects of the waste management, to evaluate the efficiency of different circular economy-driven end-of-life strategies for wind turbines operating in Greece.

3 Challenges

This section presents the technological, economic, environmental, regulatory, policy-making, cultural, and social challenges confronting the offshore wind energy industry with respect to circular economy development.

3.1 *Technological*

Technology plays a vital role in supporting the transition to circular economy models by enabling businesses to collect and analyze data, track resources, and reduce waste generation and disposal. Examples of technologies that can support the circular economy transition include sensors, cameras, RFID tags, mobile applications, and connectivity technology such as 5G and Internet of Things (IoT). These technologies can enable the wind energy industry to track and monitor the lifecycle of wind farm assets and collect and analyze real-time information about their status. This will help to identify when a component needs to be repaired or replaced and determine which end-of-life strategy is most effective in reducing waste disposal.

In the recent Industry 4.0 era, lack of technological adoption and access to personnel with digital expertise are the main challenges that the wind energy industry faces in successfully implementing circular economy practices. For example, some technologies such as 3D printing or additive manufacturing, robotics, Artificial Intelligence (AI) and Machine Learning (ML), cloud computing, blockchain, and augmented reality (AR) can support the circular economy transition, but they have not yet reached their full potential in the offshore wind energy industry due to various reasons such as the lack of appropriate supporting tools and infrastructures.

3.2 *Economic*

Offshore wind energy is still an expensive energy technology, and its capital costs are higher than other low-carbon energy technologies. The circular economy can generate significant economic benefits to the offshore wind industry, helping it to bring down levelised cost of energy (LCOE) and make itself a more competitive source of energy. Circular economy can create new supply chains and revenue streams by preventing waste from ending up in landfills, extracting useful materials and parts, and reselling the second-hand components or recycling them for further use. Nevertheless, the economic benefits of circular economy are not directly visible and there are very few business models that can be utilized to assess the economic effects of different circular economy strategies in the offshore wind industry.

3.3 *Environmental*

The circular economy transition would offer many environmental and ecological benefits to the offshore wind industry, such as protection of marine ecosystem, preservation of marine resources, and reduced greenhouse gases emission. However, the environmental impacts of circular economy in the offshore wind industry are not fully understood and thus not represented in the current business models. This can be challenging to measure the environmental impact of circular economy with the absence of a consensus on a standardized methodology for life cycle assessment (LCA).

3.4 *Regulatory*

Regulations play a key role in the wider adoption of circular economy business models. Knowledge of regulations such as the EU's Circular Economy Action Plan (CEAP) [7] and the UK's waste management law and practice [15] are prerequisites for succeeding in the transition to a circular economy. CEAP introduces a set of legislative and policy measures to help businesses address the challenges of transitioning to a circular economy. The UK's Circular Economy Package (CEP) also introduces a legislative framework that identifies clear steps for the reduction of waste and establishes a long-term path for waste management and recycling. Nevertheless, there are some barriers in regulations for the transition of circular economy in the offshore wind industry. The sector will need experts in national and EU regulation as well as competence in how to influence processes and development trends. An integrated analysis of regulatory barriers and economic incentives is required, in order to support circular economy alternatives.

3.5 *Policymaking*

Government policies highly influence the adoption of circular economy, both nationally and globally. Governments play a crucial role in encouraging innovation and new initiatives for material recycling. They can provide platforms for idea exchange and cooperation between industries and improve awareness over circular economy. In recent years, the EU has had a leading role in advancing public policies on circular economy. However, some specific industrial policies will be required to act as guidelines for circular economy development in the offshore wind energy sector.

3.6 *Cultural*

The fundamental idea of the circular economy is to move from the perception of ‘waste as a problem’ to the perception of ‘waste as a resource’. Culture plays a critical role in the success of circular economy models. Therefore, culture must not be left behind in the circular economy transition. The major cultural barrier identified for the deployment of circular economy in the offshore wind industry is not having the sense of urgency and lack of interest and awareness.

3.7 *Social*

For the circular economy transition to succeed, high levels of cooperation from all sectors of society will be needed. Collecting high quality waste streams for re-use, remanufacturing and recycling requires citizen engagement and social accountability.

4 Opportunities

Industry 5.0 is a new concept that builds upon the principles of Industry 4.0 and mainly focuses on a sustainable, human-centric, and resilient industry. With the development of Industry 5.0, many new advanced technologies have emerged to help businesses manage the circular economy transition more effectively and efficiently. Some of the Industry 5.0 technologies include IoT gateways, cyber-physical systems, cloud computing, blockchain, big data analytics, 6G networks, augmented reality (AR) and virtual reality (VR), artificial intelligence (AI), machine learning, digital twins, condition-based monitoring, and enterprise resource planning (ERP) [16]. Figure 2 presents the applications of Industry 4.0/5.0 technologies in offshore wind circular economy.

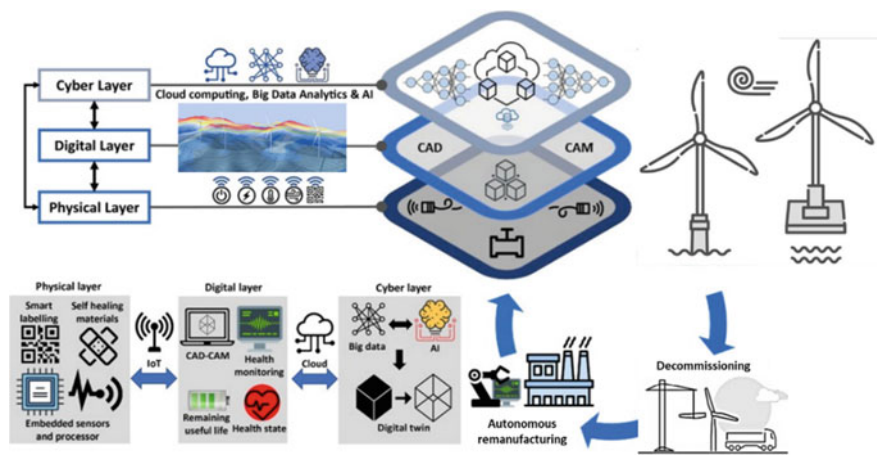


Fig. 2 Applications of Industry 4.0/5.0 technologies in offshore wind circular economy [17]

In this section, we propose some of the opportunities that Industry 4.0/5.0 can offer to the wind energy industry with respect to circular economy development and growth.

4.1 IoT-Based Smart Waste Management Systems

IoT based waste management systems can offer significant opportunities to the offshore wind industry to effectively manage end-of-life wind turbines via the integration of sensor technologies and data modelling. IoT systems can continuously monitor waste streams in real-time, optimize collection routes, and promote better recycling and reusing practices [18]. Data collected from IoT systems can also give the industry an accurate view of the type of waste generated and if possible, its composition.

4.2 Automating Image Analysis for Waste Classification and Recycling

Advanced sorting and recycling technologies, such as optical sensors and AI-powered systems, can enable the offshore wind industry to efficiently separate and process different waste materials. Automated image processing is a method, such as convolutional neural networks (CNN), by which waste images can be analyzed and processed in an automated manner. This method can help system operators gather the images or videos from a camera with object recognition, detection, and prediction, and

then categorize the waste materials into different groups such as biodegradable, non-biodegradable, recyclable, etc.

4.3 Through-Life Assessment of Circular Economy Strategies

A through-life assessment is crucial because a circular economy model may have lifecycle implications. Lifecycle assessment (LCA) can support circular economy by providing a holistic and transparent view of the economic, environmental, and social benefits. Industry 4.0 technologies such as ERP can enable dynamic LCA and monitoring of waste materials in the offshore wind energy sector.

4.4 Robotic Remanufacturing and Recycling of Components

Robotic remanufacturing and recycling will be a key focus in the future of the circular economy. Robots can substantially support the circular economy transition by reducing waste materials, optimizing the use of resources, and promoting the reuse and recycling of components. There will be a wide range of robots for materials reusing and recycling in the offshore wind industry. Therefore, human–robot collaboration plays an important role in robotic remanufacturing.

5 Conclusion

“Circular economy” is a new area of research that has recently attracted a lot of attention in the offshore wind energy industry. However, it has been little implemented in practice due to several financial, structural, operational, attitudinal, and technological barriers. This paper presented an analysis of the barriers confronting the offshore wind energy industry in the transition to a circular economy. Several Industry 4.0/5.0 technologies and tools were also identified to support circular economy initiatives in the offshore wind energy sector. One of the ways in which Industry 4.0/5.0 can support the circular economy is through the design of multi-functional and self-healing composite materials for wind turbines. These materials can be used for a longer period and repaired or upgraded more easily. Sensors and other technologies such as RFID and IoT can play a key role in tracking and monitoring the lifecycle of components. Creating an automated waste detection system using a deep learning algorithm is also an intelligent way to classify wind turbine waste.

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Industry 4.0 Support of Remanufacturing Operations



A. Dimitrokalli , G.-C. Vosniakos , P. Benardos , and E. Matsas

Abstract Remanufacturing has emerged as a pivotal practice in the pursuit of sustainable manufacturing but it is facing challenges, including decision complexity, ergonomic concerns, and assembly and disassembly plan efficiency. This paper introduces a framework for advancing remanufacturing processes emphasizing Industry 4.0 (I4.0) concepts with special focus on Virtual Reality (VR) as exemplified by three applications. The first one leverages an armband motion sensor for intuitive programming of a robot, demonstrating potential enhancements in programming robotic tasks involved. The second one introduces VR for automated ergonomic assessment in remanufacturing tasks involving the human, using standard protocols. The third one explores VR-based evaluation and guidance of collaborative assembly plans by human and robot.

Keywords Remanufacturing · Virtual Reality · Sustainability · Ergonomic Assessment · Circular Economy

1 Introduction

In the contemporary pursuit of sustainable and environmentally friendly practices, End of Life (EoL) activities have garnered significant attention. Factors such as escalating energy and material costs, the scarcity of rare earth metals, increasing consumer demand for environmental consciousness, and legislative pressures on businesses have propelled the development of EoL business practices. Among these practices, remanufacturing stands out as a potent and expanding field [1].

Remanufacturing, as defined by BS 8887–220:2010, involves transforming a product into an as-new state with performance and warranty equivalent to new [2]. Distinguished from other forms of reuse by its completeness, remanufacturing delivers end products of superior quality, meeting customer expectations as if brand

A. Dimitrokalli · G.-C. Vosniakos (✉) · P. Benardos · E. Matsas
School of Mechanical Engineering, National Technical University of Athens, Iroon Polytechniou
9, 15773 Athens, Greece
e-mail: vosniak@central.ntua.gr

new. As a sustainable business strategy, remanufacturing excels in reclaiming and repurposing materials while preserving the embodied energy of the original product, reducing resource consumption and waste and aligning with circular economy principles [3]. Originating during the Second World War in the USA as an efficient method to produce and maintain heavy machinery [4], remanufacturing has evolved to serve diverse industrial sectors globally [5], with projected significant contribution to EU economy [6].

The advent of Industry 4.0 (I4.0) marks a new era by intelligently networking machines and processes and by facilitating data exchange between physical and virtual devices through the Internet of Things (IoT) [7]. While the smart factory is well-established, remanufacturers, operating in a distinct lower technology environment than normal manufacturing with unique management strategies [8], require a tailored I4.0 vision [9]. In this direction, this paper proposes support in planning and execution of remanufacturing operations by I4.0 technologies focusing on Virtual Reality (VR), sensors and custom software as a representative demonstrator.

2 Challenges in Remanufacturing

Factors such as product design, parts availability, market demand, condition of returned parts are important for remanufacturing. Unlike recycling, remanufacturing involves a substantially higher investment, necessitating a thorough assessment of the viability of remanufacturing, considering practical, financial and environmental aspects. While remanufacturing and normal manufacturing share similarities in methods, machinery, and batch production, remanufacturing introduces greater complexity [10]. Challenges arise from core availability (part or whole used product), timing, demand, and quality. Core quality is crucial as it dictates remanufacturing steps and resources.

The remanufacturing process comprises 7 key activities: core acquisition, inspection/grading, disassembly, cleaning, reconditioning, reassembly, and testing. Mechatronic or electronic products designated for remanufacturing necessitate an initial diagnostic test to assess functionality or defects. Decision points at each stage impact subsequent activities, resource allocation, and overall success [11]. Remanufacturing so far stands apart from normal manufacturing due to its continued reliance on labor-intensive processes. Decision-making in remanufacturing often requires ad-hoc engineering expertise, relying on technically skilled engineers or technicians. Lack of standardization and suitable nondestructive testing methods for reused/repaired parts as well as absence of original design specifications, Middle-of-Life usage information and repair history add to the complexity [12]. I4.0 is poised to address some of these challenges.

Unlike previous automation focusing on single machines and processes, I4.0 facilitates end-to-end digitalization of all processes and physical assets across the entire supply chain [13]. I4.0 can also help streamline decision-making in intermediate remanufacturing activities. Furthermore, smart technologies integrated into products

or equipment, coupled with enabling technologies such as robotics, big data analytics and Artificial Intelligence (AI), can present viable or optimum remanufacturing processes.

Known I4.0 key approaches include the integration of product life data with AI algorithms for dynamic decision-making and the application of VR for planning and simulation. VR applications span planning, execution and evaluation activities through a dynamic, immersive environment for task visualization, training, and ergonomic assessment. Indicative applications are presented next.

3 Applications of I4.0 Tool Development for Remanufacturing

3.1 VR-Based Robot Movement Teaching by Armband

Use Case. An armband motion sensor empowers the control and ‘intuitive’ programming of a classic robotic arm with precision. The robot used is a 6-axis StäubliTM RX 90L with an in-house developed pneumatic gripper, Fig. 1. The user can guide by demonstration the arm to grasp, move, orient and place objects with respect to surfaces. These are potential building blocks for robot programs for assembly and disassembly tasks in remanufacturing. Initially, rigorous testing was scheduled in a virtual environment serving as a simulation platform where potential collisions and other errors were detected and rectified. The virtual environment provides a safe space to refine the armband’s commands and coordinate the operator’s gestures and the robot’s movements.

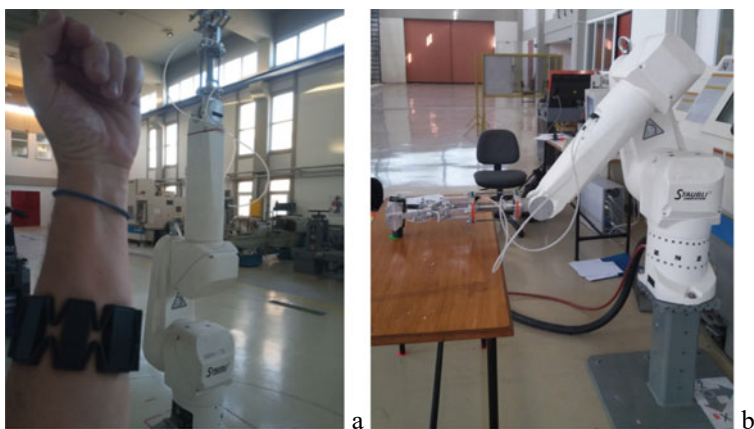


Fig. 1 Robotic arm **a** programmed by Myo Armband **b** executing a placement task

System Setup and Configuration. For the virtual simulations, scenes were constructed within Unity3D 3D™ environment and executed on a PC operating Windows 10™ 64-bit and equipped with an AMD™ Radeon R9 290 graphics card and a Myo armband™ sensor connected to the PC via Bluetooth, see Fig. 1a.

The Myo armband is equipped with a nine-axis Inertial Measurement Units (IMU), encompassing a three-axis gyroscope, three-axis accelerometer, and a three-axis magnetometer. Thus, it accurately detects orientation and motion of the human forearm. Additionally, utilizing EMG sensors it captures electrical activity from muscles to discern five distinct predefined/default hand gestures. The sensor's data is displayed in real-time on the computer screen as well as being stored in its hard drive for analysis. Additionally, the user receives feedback through vibration and sound alerts connected to specific conditions. Communication between the sensor and Unity3D environment was established using the sensor manufacturer's SDK. Rigorous testing was conducted to refine accuracy, filter noise through scripting, as well as fine-tune data frequency.

Experiment. The scenario encompassed precise picking-and-placing an object by the robotic arm, ensuring correct orientation within a tightly specified space. A tailored virtual scene was constructed, featuring the robot and all objects involved, see Fig. 2a. Interactions between objects and surfaces were simulated using C# scripts, seamlessly integrated in the Unity3D platform.

The user was tasked with relocating the object from the designated blue zone to the green zone. Any detected collisions involving robot components or the object with fixtures or other physical constraints triggered immediate alerts via armband vibrations, visual cues, and auditory signals. Additionally, various angles were simultaneously monitored to expedite object placement for convenience, see Fig. 2b.

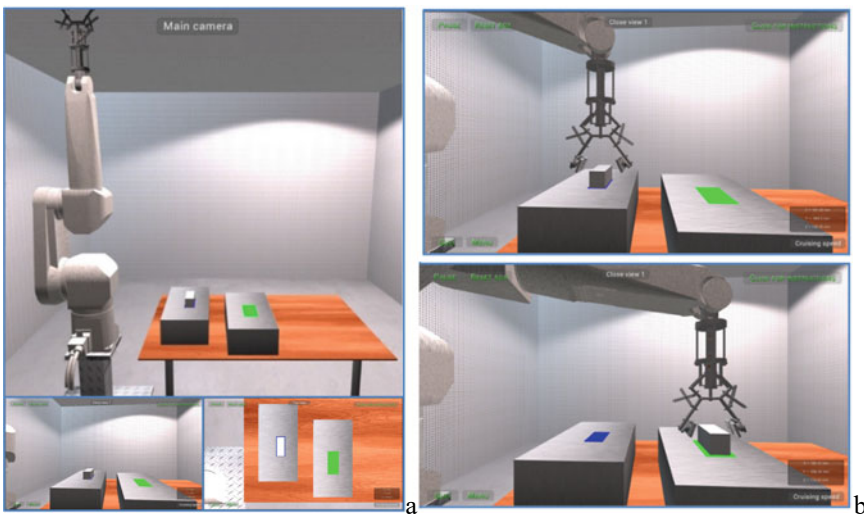


Fig. 2 VR environment **a** design **b** displaying pick and place task

Table 1 MyoMover precision test results (object completely inside/partially inside or outside the required area is denoted by green/yellow and red color respectively)

Test	1	2	3	4	5	6	7	8	9	10	Success rate
Experienced User	Green	Green	Green	Yellow	Green	Yellow	Green	Green	Yellow	Green	100%
Beginner 1	Green	Yellow	Yellow	Green	Green	Yellow	Green	Green	Yellow	Green	90%
Beginner 2	Yellow	Green	Green	Green	Yellow	Green	Green	Yellow	Green	Green	90%

Following successful virtual trials, the identical scenario was executed with the real-world robot, employing pre-validated scenario implementations entailing recording the end effector’s and joint coordinates during the VR run and subsequently transferring them into V + programming for the robot to execute in reality. Speed parameters were adjusted, encompassing cruising speed and precision speed, to uphold safety standards.

Results. The virtual scenario underwent testing with three subjects, one experienced and two beginners, who received basic training on utilizing the armband, each completing a total of 10 repetitions. Notably, any instances of failure were primarily attributed to the acclimatization process. After 2–3 attempts, participants demonstrated a clear understanding of the scene mechanics, resulting in successful test execution, see Table 1. Subsequently, data from these tests were saved and employed for the actual robot programming in V + . This necessitated the use of a shared coordinate system between real and digital environments. Furthermore, it was imperative to align the real-world scale and positioning of the table and box with their counterparts in the Unity3D scene.

Conclusions. A novel approach was introduced to robotic manipulation of objects involved in remanufacturing workflows through the integration of an armband motion sensor, allowing intuitive task programming. Rigorous testing and tuning is required to ensure safety and refinement of commands and achievable accuracy.

3.2 VR-Based Automatic Ergonomic Assessment

Use Case. Creating a VR environment for automated ergonomic assessment using the Rapid Upper Limb Assessment (RULA) scale offers a transformative solution for workplace safety and efficiency. This approach involves designing a virtual scene to mimic real-world work conditions. Workers perform tasks within this VR environment, allowing for a comprehensive evaluation of their postures and movements, which is then automatically assessed against the RULA scale criteria. Conducting tests in a controlled environment ensures precise calibration of equipment and external variables, ensuring the highest level of accuracy in data collection. This methodology is particularly valuable in industries with repetitive or physically

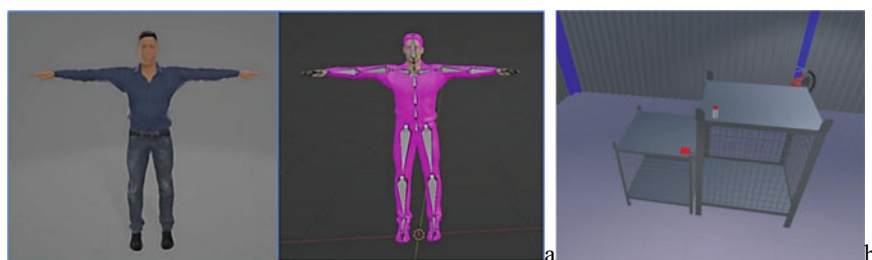


Fig. 3 **a** Virtual avatar and rigged skeleton **b** Virtual scene for experimentation

demanding tasks, as it systematically identifies and mitigates ergonomic risks, ultimately creating safer and more efficient manual work environments such as those of remanufacturing operations.

System Setup and Configuration. The virtual simulations were constructed in the Unity3D™ environment running on a Windows11™ 64-bit system. A Kinect2™ motion sensor captured body movement and transmitted it to the PC via USB, providing real-time communication with Unity3D through the Microsoft Kinect SDK 2.0. MakeHuman™ software was employed to craft and customize the avatar's external appearance, while Blender™ was utilized to implement digital skeleton creation (rigging) for lifelike avatar movements, see Fig. 3.

All interactions between avatar and virtual environment were coded in C# in Unity3D and appropriate filtering and data handling were implemented. RULA method was employed for ergonomic assessment, gauging biomechanical stress on the worker's upper limbs and pinpointing the muscular effort associated with specific working postures. Such assessment is largely based on continuously measuring posture angles of the avatar and averaging them in time as indicated by RULA rules.

Experiment. A test scenario was devised to evaluate automated RULA scoring routines developed. To account for motion sensor limitations, attention was given to ensure that body parts did not overlap during distinct movements. A starting position with zero negative scoring was established, and the trial commenced once the tester assumed the correct posture. Specialized buttons were introduced to furnish crucial data for ergonomic assessment, such as the object's weight and the availability of lower body support, as the sensor solely covered upper body movement.

The scenario entailed picking up a basic cylindrical object from a raised horizontal surface at a height of 1.5 m, then rotating it 180 degrees to ensure proper orientation before placing it on a table at a 1 m height with the red surface touching the table, see Fig. 3b. Upon successful completion of each trial, an automated message displayed the total RULA score, along with individual scores for each component. A color-coded scaling system was also integrated for user-friendly interpretation, see Fig. 4.

Results. The experimentation phase yielded promising results in the assessment of ergonomic performance using the developed application. Multiple trials involving diverse test subjects were conducted, during which the application consistently

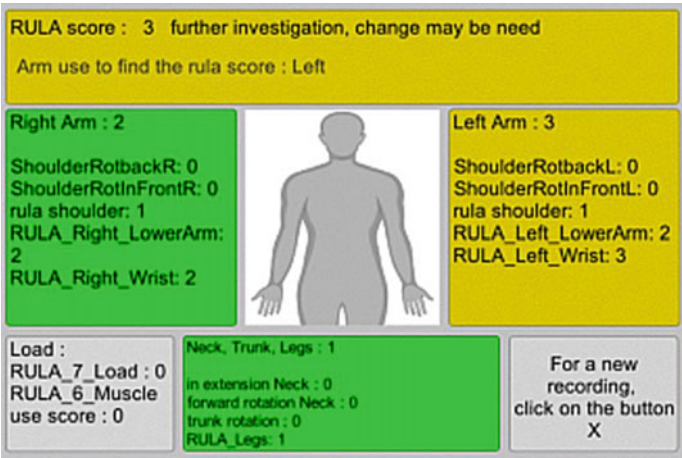


Fig. 4 RULA scoring as an automatic pop-up after test completion

computed RULA scores based on input parameters, including angle measurements and timings. The systematic examination of subsequent files, encompassing varied scenarios, affirmed the robustness and reliability of the application.

Conclusions. Feasibility of automatic ergonomic assessment in a virtual environment, in this case utilizing the RULA scoring system, was demonstrated. This virtual assessment method can very efficiently be used in remanufacturing to ensure ergonomic efficiency, minimizing strain on workers. It enables precise evaluation of movements, aiding in task planning and process optimization for a safer, more efficient remanufacturing process. Further testing is anticipated, involving real-life ergonomic experts, to establish a comparative analysis between virtual and real-world assessments. Additionally, a subsequent phase of experimentation is envisioned, wherein individuals undergo multiple virtual trials to assess improvement in ergonomic scores over time.

3.3 VR-Based Assembly Plan Evaluation

Use Case. The study explores two simultaneous scenarios involving the assembly of a filament winding robotic head consisting of 22 distinct components, see Fig. 5 [15]. In the first scenario, the work is being completed solely by the human while in the second one human-robot teamwork is incorporated. The emphasis lies in the meticulous examination of the assembly procedure, contrasting situations with and without robot involvement, and evaluating their respective implications on time efficiency and ergonomic considerations gathered from the participants. It is imperative that all necessary components undergo assembly in a precise sequence and orientation.

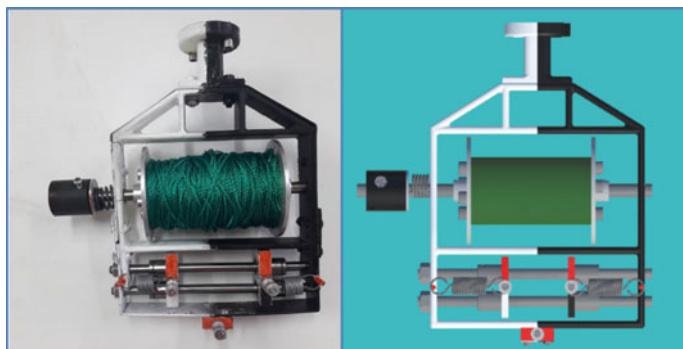


Fig. 5 Real-life and virtual model of prototype winding head

VR support is tested for evaluating assembly plans in remanufacturing, communicating these plans effectively to the human workforce involved and providing training instructions required for implementing these plans. Thus, it allows for iterative improvements before implementation leading to cost savings and optimized operations.

System Setup and Configuration. The virtual simulations were conducted within the Unity3D environment, operating on a Windows 8.1 64-bit platform equipped with an AMD Radeon R9 290 series graphics card. This experimental framework comprised a PC unit, a Leap Motion sensor, and an Oculus Rift DK2 stereo headset. Data transmitted from the sensor and headset were conveyed to the computer system via USB interfaces. The stereoscopic imagery was transferred and projected onto the user's headset at the same time through a contemporaneous HDMI link, see Fig. 6. Communication with the Leap Motion sensor with Unity3D was established through the manufacturer-endorsed Software Development Kit (SDK) v. 3.1.3. In order to mitigate potential vulnerabilities in sensor performance, any form of direct natural or artificial lighting on the subject was deliberately excluded and all distances were carefully optimized in accordance with the specifications provided by the manufacturer.

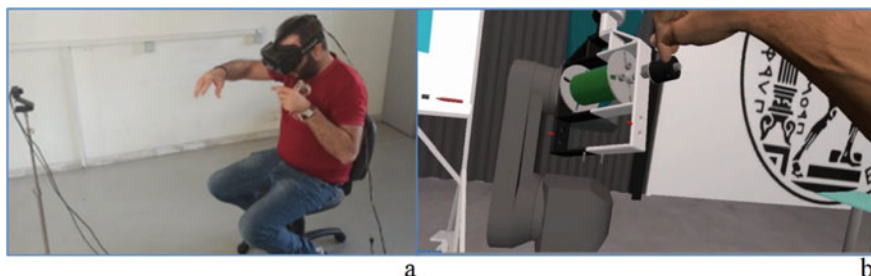


Fig. 6 Assembly scenario execution **a** real-life **b** virtual

The virtual scene was created as a replica of an actual setting with a 6-axis robotic arm. In the non-cooperative scenario, the robot serves as a stationary prop. The setup includes a 3D model of a filament winding robotic head, a Stäubli RX90L robotic arm, avatar hands for participant interaction, and real-time data exchange with the headset and motion sensors. Interactions with 3D elements are tailored for each scenario and programmed through C#. Task timing and wrist position calculations were performed by simple mathematical formulae. A total of 39 scripts with 5400 lines of code were developed.

Experiment. The assembly sequence was initially determined by necessity, followed by a logical grouping of similar tasks, resulting in the first scenario. High wrist strain steps were identified and recommendations from literature on reducing CTS risk factors were applied. This led to task redesign, including adjusting workstation height and providing retainers/clamps. Robot movements were then introduced to align with these ergonomic guidelines, although additional movements were required for optimal positioning. The collaborative scenario included these extra robot steps, while the remaining 22 assembly steps were consistent with the first scenario.

To mitigate potential user unfamiliarity with the process and its distinct steps, each scenario was executed three times with every participant. The scoring from the final trials for each step along with precise timing recorded eliminated any uncertainties.

During experiments, wrist movements were tracked using Leap Motion sensor and Unity3D properties to assess ergonomic impacts of human–robot collaboration. Data encompassed wrist rotation, position, and distance from torso in a 3D environment. A modified version of the RULA scale (see Fig. 7) was employed to evaluate hand movements, categorizing them as no risk, low, medium, or high risk. Note that steps categorized as ‘high risk’ necessitate immediate modification. This comprehensive analysis allows for informed improvement in the assembly process.

Results. Two groups, each comprising 12 final year Manufacturing Automation students tested each scenario. No subject was in both groups. A 15-min instruction session preceded the assembly task, instructions being displayed on a virtual screen during execution in both scenarios ensuring uniformity and minimizing confounding factors.

In the first scenario, the robot serves as a fixture, holding the robotic head frame rather than participating in the assembly process. Data from 10 out of 12 participants were considered, outlier data being excluded. In the second scenario, collaboration between the robotic arm and human is introduced. The robot’s role is to position

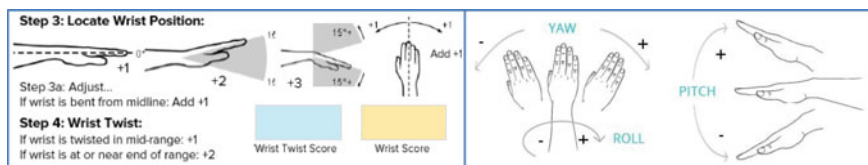


Fig. 7 RULA scale for wrist assessment

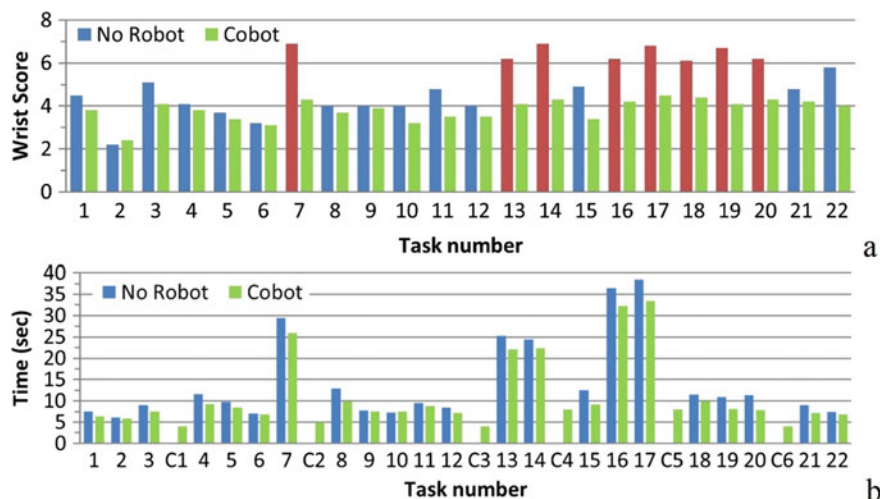


Fig. 8 Scenario comparison with and without robotic assistance. **a** Ergonomic assessment **b** Task completion timing

and orientate the already assembled parts, minimizing human wrist rotation and task distance for the new parts added to the assembly.

Figure 8a displays the mean scores for each task. Tasks with a score of 6 or higher, highlighted in red, indicate high risk and require immediate improvement. Figure 8b presents the mean duration for assembly tasks. Tasks which previously had an average score above 6 have since improved by exploiting collaboration with the robot and are highlighted in green.

The results highlighted the substantial impact of a collaborative robot, on mitigating wrist strain. Indeed, the absence of an average risk coefficient exceeding 6 indicates absence of high-risk tasks. The comprehensive average risk coefficient stands at 111.1 without robot participation diminishing to 84.2 with robot involvement, representing a notable 24.2% reduction in wrist strain. In terms of completion time, the robot-assisted scenario corresponds to an average of 303.3 s, compared to the robot-free case at 313.6 s. Despite the robot's 33-s contribution, the cobot leads to increased completion speed, thereby offering a productivity advantage.

Conclusions. The study introduces a tailored ergonomic scoring method that effectively quantifies task-related risks. The virtual environment showcased reduced wrist strain and heightened assembly efficiency with cobot support. These findings hold direct relevance for remanufacturing processes, offering a promising way to enhance productivity and address ergonomic concerns.

4 Conclusions and Outlook

Remanufacturing is vital for sustainable and environmentally conscious manufacturing, yet encounters challenges in flexible robotic support of human-driven operations, ergonomic concerns, and efficiency of assembly/disassembly plans. This paper presents a framework focusing on VR and addressing these challenges using sensors and software for calculating crucial parameters for assessments and decision making.

The first tool integrates an armband motion sensor, promising flexibility in designing robotic support of operations. The second tool demonstrates how automated ergonomic assessment can be achieved. The third tool demonstrates comparison of alternative assembly plan scenarios, in this case revealing the advantages of human–robot collaboration.

Collectively, these experiments showcase the immediate applicability of VR technologies coupled with task specific sensors and related computations in remanufacturing, laying the foundation for improvements, streamlining and eventually standardization and optimization of the pertinent operations. The framework emphasizes flexibility, safety, and efficiency, which are still missing in remanufacturing practices. Future research should expand on these applications validating the full potential of the pertinent technologies in advancing remanufacturing.

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The Remanu-Leasing Model Towards a Convenient and Sustainable Product Circularity



Francesco Mancusi , Fabio Fruggiero , and Duc Truong Pham

Abstract In recent years, a circular economy model has been established to promote sustainability. The model supports a service-oriented approach where leasing-based strategies can be applied to part and component use (multiple use) and recovery and rearrangement. Product leasing can recreate value in each cycle for both the lessor (i.e., remanufacturer) and the lessee (i.e., consumer). Nevertheless, there is not a clear vision/perspective about the effectiveness in sustainability of a leasing-based model in terms of a product's environmental impact. Furthermore, the benefits generated by the leasing contract should be balanced between the involved agents. In this work, the authors introduce the concept of remanu-leasing, proposed as the optimal configuration of a leasing contract aimed at balancing and maximising lessor and lessee interests while minimising the product's environmental impact.

Keywords Remanufacturing · Leasing · Circular economy · Optimisation

1 Introduction

Governments are adopting green policies aimed at reducing waste and carbon emissions, such as the EU CEAP [1], the Green Deal [2] and the U.N. 2030 Agenda [3], resulting in sustainable strategies such as extended producer responsibility (EPR) [4]. Such a scenario is forcing firms to take care of the entire product lifecycle, including multiple reuses and final disposal. This led to adding to the forward process (i.e., take-make-use-dispose) a reverse flow of returning end-of-life/use (EOL/U) durable products, involving their collection, recovery and remarket. However, such a closed-loop supply chain (CLSC) [5] turned out to be a more complex network [6, 7] than the traditional forward supply chain, as it is affected by many more uncertainty drivers

F. Mancusi (✉) · F. Fruggiero

School of Engineering, University of Basilicata, 85100 Potenza, Italy
e-mail: francesco.mancusi@unibas.it

D. T. Pham

Dep. of Mechanical Engineering, University of Birmingham, Birmingham B15 2TT, UK

[8]. After all, it is well known that those uncertainties blur the planning of timing, costs and resources for reverse logistics, disassembly and recovery operations [9–12]. Although the support of Industry 4.0 technologies has allowed the implementation and management of complex circular models, recent extraordinary circumstances have highlighted the current industrial systems' critical dependence on raw materials, the shortage of which can lead to their collapse [13]. This further reinforces the need to manage EOL/U products and, therefore, the centrality of the consumers' behaviour as a main uncertainty driver. Studies have focused on the possibility of controlling or actively involving them in the CLSC to reduce uncertainties in EOL management [14, 15]. The potential of the leasing strategy is well known in the literature as an enabler for the circular supply chain [16], improving both customer service and uncertainty control [17]. However, strategic decisions concerning end-of-leasing matters are strongly influenced by the issue of the actual economic value of the exhausted item. For example, damage conditions and technological obsolescence may exclude sustainable-but-not-profitable “new life” alternatives. This motivates the authors to investigate the optimal configuration of a leasing model with multiple use cycles to shed light on the benefits for the lessor, the lessee and the environment.

This chapter is structured as following. In Sect. 2, current knowledge on the leasing of remanufactured products is summarised, and the environmental impact of a product is discussed. In Sect. 3, we introduce the concept of remanu-leasing and present its mathematical model. In Sect. 4, the future development and potential of the proposed model are discussed.

2 The Opportunity for Leasing in Multiple Product Use Cycles: Actual Knowledge and Contribution to the Purpose

The majority of the literature about leasing is concerned with its economic convenience versus selling while considering the leasing of new (i.e., the first use-cycle) products.

A deep search of the Scopus database has revealed that very few studies have investigated the issue of leasing remanufactured products. The search string “*leasing*” OR “*lease*” AND “*remanufactured*” within “article title, abstract and keywords” (updated April 2023) generated only 22 documents. We analysed the database by reading the title and abstract of each document to exclude those out of context, not written in English, or duplicates. After that skimming, the documents of interest were reduced to 14. The paper reading revealed that only 9 of those concerned specifically the leasing of remanufactured equipment. It should be remarked that 5 out of the 9 came from the same authors.

In the first approach, we objectively analysed the selected documents. Subsequently, we reviewed each paper in terms of contribution to our goal of configuring an optimal leasing contract for multiple use cycles of remanufactured items by maximising and balancing the benefits for the consumer/lessee, remanufacturer/lessor and environment.

2.1 Literature Analysis and Content Review

Thurston et al. [18] proposed a mathematical model for making decisions about the optimal leasing period for computer components. In three market segments (technophile, utilitarian and green consumer), the model is aimed at maximising the overall satisfaction. That is, maximise product reliability, minimise leasing cost and minimise environmental impact. While the study is exhaustive on the definition of customer utilities, it does not analyse the benefit for the lessor.

Iskandar et al. [19] investigated how to balance the lessor's and the lessee's interests in a multiperiod lease contract for a remanufactured item. Those interests are, respectively, for the lessor to find the optimal recovery and maintenance efforts maximising the profit and for the lessee to select the most convenient option. They proposed a mathematical model for joint optimisation. The same research group investigated issue modelling of the decision problem as a Stackelberg game [20] and as a Nash game [21]. In [22], they focused on the quantification of the downtime of the leased remanufactured while investigating the optimal condition based maintenance policy—and inspection period—for maintaining a lease remnant product [23]. Despite the remarkable contribution of those authors, in their work, the environmental impact of leasing configurations is never taken into consideration.

Hajej et al. [24] studied the optimal lease agreement for a closed-loop hybrid system (manufacturing + remanufacturing) with and without a predictive maintenance monitoring contract. The modelling of the leased product failure rate—based on the cumulative stress of use—is significant, as it led to the introduction of a remanufacturing degradation factor. This allows us to estimate the EOL quality and, thus, the recovery effort needed. The environmental impact in terms of emissions for each leasing period was also considered. For our purpose, the work is limited by the single perspective, i.e., that of the lessor/remanufacturer, aiming at minimising costs.

Ohgren et al. [25] reported the actual state of product service system (PSS) perception in the field of the reconditioned furniture industry. They collected data by interviews with furniture reconditioners and public practitioners. The result was that leasing solutions are able to give environmental benefits, stimulate PSS-oriented solutions and innovation, and improve OEM revenues. The article only conceptually contributes to our aim, also introducing the furniture category for leasing.

Mutha et al. [26] investigated from both the financial and accounting perspectives the optimal lease price for multiple use-cycle remanufactured capital-intensive products. The gap between the accounting and the financial life (and profit) of a remanent leased product acts as an uncertainty driver in determining the optimal lease price.

A valuable contribution is the analytical definition of the economic value of leasing use cycles. Regardless, this work only considers the benefits for the remanufacturer/lessor, neglecting those of the consumer and the environmental impact.

The literature review confirms the need for a comprehensive model able to compare the consumer's and remanufacturer's needs in a sustainable product-based arrangement. Our proposal is to select the main features and best configuration in the optimal "remanu-leasing" contract, i.e., (i) maximisation and balancing of the interests of the lessor/remanufacturer and lessee/consumer and (ii) minimisation of the overall environmental impact of the product. Particular attention must be paid to the degradation model of the leased product, which enables the determination of the periodic maintenance plan and the intensity of recovery operations at the end of each use cycle.

Much of the discussion about the convenience of the leasing model involves electronic equipment or automotive use cases. These product categories have a high environmental impact not only in their (re)manufacturing phase but also during their operation, raising doubt about the effective sustainability of leasing compared to selling [27].

Life cycle assessment (LCA) is a well-known method for assessing environmental impact in each phase of a product's life cycle, from raw material extraction through to final disposal [28]. Any product subject to consumption has a certain amount of environmental impact (EI) due, respectively, to the first stage of procurement of raw materials or components, then manufacturing, usage phase and EOL management [29]. Transport, which evolves across all phases, also increases the impact. A method has been proposed to evaluate which phases of the product life cycle have the heaviest environmental impact, therefore requiring greater (and greener) effort in the life cycle design [26]. For instance, if at a certain time, the EI of the usage phase is greater than the EI of the EOL management phase (i.e., disposal), then the prolongation of the useful life would lead to a greater environmental impact than disposal (e.g., multiple lease use cycles of a polluting car, not compliant with the latest green standards). Therefore, product circularity does not necessarily gain environmental sustainability. This requires the assessment of the overall environmental impact of the product.

3 The Remanu-Leasing Model

The remanu-leasing approach concerns the optimal configuration of a leasing contract for remanufactured products, with the objective of maximum benefit, for the lessor and the lessee, and minimum environmental impact. The context of application is the CLSC in which the lessor is the remanufacturer and the lessee is the consumer (end-user). The benefit is defined in terms of consumer surplus (CS) and remanufacturer surplus (RS). The environmental impact (EI) is defined in terms of the global warming potential (GWP).

Modelling the degradation of the product during the use stage plays a central role in the model. Pessimistic forecasts may lead to an early conclusion of the use cycle,

with greater environmental impact (due to early remanufacturing), as well as lower profit for the lessor. On the other hand, optimistic forecasts would increase the risk of failure during use, thus reducing field reliability—customer service—and increasing remanufacturing costs. Persona et al. [30] introduced the mathematical function of systemability as a random variable for predicting the field reliability based on actual operating conditions. In particular, the systemability approach has the potential to correlate the effects of environmental conditions (i.e., environmental stressors) and intensity of use (i.e., usage stressors) with product degradation during the use phase. Therefore, a realistic—and highly reliable—prediction of the frequency (and cost) of routine maintenance (minimal repair) can be assessed.

4 Problem Formulation

p	Product type
θ_p	Product list price if purchased
i	Annual inflation rate
T	Total duration of lease (years)
t	Lease unit period (year)
u	Usage stressor
u_s	System-ability intensity function
e	Environmental stressor
P_m	Average price of maintenance (minimal repair)
$P_L(t)$	Leasing periodic fee including maintenance
RV	Residual value of the product at the last period
$R_L(t)$	Revenue from leasing per period
R_S	Revenue from selling
C_R	Total cost for recovery at the end of use-cycle
C_m	Maintenance cost at minimal repair condition
C	Number of use-cycles
n_C	Number of maintenance calls (function of usage and env. stress)
p_R	Price of maintenance (type and intensity function of usage and env. stress)
$d(T)$	Depreciation (value in of percentage loss) at year T
$PLV(u, e)$	Permanent loss of efficiency (non-repairable) due to usage and environmental stress in percentage of product price
EI	Product total environmental impact
EI^{uc}	Product total environmental impact per use-cycle
EI_P	Environmental impact of raw material procurement
EI_M	Environmental impact of manufacturing

(continued)

(continued)

$EI_U(T)$	Environmental impact of usage phase (cumulative in period T)
$EI_{EOL}(T)$	Environmental impact of end-of-life management assessed at period T
W	Amount of different raw materials in the product
M_w	Mass [kg] of raw material w
Y	Number of (re)manufacturing stages
MEC	Maintenance expected cost
UEC	Unit expected cost
GWP_w	Global Warming Potential due to the extraction of raw material w [kgCO ₂ e] per kg raw material
GWP_y	Global Warming Potential due to the (re)manufacturing stage y [kgCO ₂ e]
GWP_U	Global Warming Potential during the useful life (usage phase) [kgCO ₂ e]
GWP_{EOL}	Global Warming Potential due to EOL option selected [kgCO ₂ e]

4.1 Consumer Surplus (CS)

Aras et al. [31] defined the notion of consumer surplus in terms of the cost difference between the reservation price that the customer would be willing to pay for buying the remanufactured product and the present value of the leasing option for the same new product. As per the state of the art, the issue of the maintenance of a consumable good cannot be neglected. We have therefore modified Aras' formulation by introducing the cost of periodic maintenance to be paid by the customer in the buying option and the residual value of the asset at the end of its useful life. In the end, the CS is the economic difference (€) between the total capitalised cost of the purchase option and the lease option (including periodic maintenance) of the same product. Equation (1) expresses the extent of the convenience of leasing compared to purchasing for the consumer. The greater the value of CS is, the greater the convenience of leasing. A CS equal to zero implies the same value of the two alternatives. Negative values imply greater value of the purchase solution.

$$CS(p, u, e, t) = \left| -\theta_p(t_1) - \sum_{t=t_1}^T \frac{P_m(u, e, t)}{(1+i)^t} + \frac{RV(u, e, T)}{(1+i)^T} \right| - \left(\sum_{t=1}^T \frac{P_L(t)}{(1+i)^t} \right) \quad (1)$$

The price of maintenance for the customer is a function of intensity of usage, environmental stress (i.e., aging) and time. In a generic condition where u and e do not affect P_m , the value of P_m increase with time.

$$P_m(u, e, t) = n_C(u, e, t) * p_R(u, e, t) \quad (2)$$

The residual value of the product depends on the depreciation and permanent loss of value (in percentage of product price over usage and environmental stressors) due to usage and environmental stress.

$$RV(u, e, t) = \theta_p * (1 - d(T)) * PLV(u, e) \quad (3)$$

Stressors are those factors that cause the aesthetic and functional degradation of the product. Husniah et al [21] remarked that the degradation of a remanufactured product is due to both age and usage when it is operated beyond the normal mode. In other words, the environmental stressor is combined with the usage stressor, which results in the variability of actual operating conditions. The RV term must therefore be calculated assuming the most appropriate degradation model in relation to the type of product.

4.2 Remanufacturer Surplus (RS)

We define RS as the difference in net present value (NPV, €) between the leasing and selling options for the same remanufactured product. The first takes into account both the cost of periodic maintenance (C_m , maintenance as minimal repair) and the cost of recovery (C_R) at the end of the use cycle.

$$RS(p, t) = \left[\frac{\left(\sum_{t=t_1}^T \left[\frac{R_L(t)}{(1+i)^t} - C_m(t) * (1+i)^t - C_R * (1+i)^T \right] \right)}{(1+i)^{CT}} * C \right] - R_S \quad (4)$$

The cost of periodic maintenance is modelled on the basis of the unit expected cost (UEC) defined by Sgarbossa et al. in an application of the systemability function [32]. Since that work referred to the periodic replacement policy, we changed the UEC to maintenance expected cost (MEC), referring to the average cost of periodic maintenance (minimal repair) according to the intensity of use and the environmental stress conditions.

$$C_m(t) = MEC_{\alpha, \beta}(t_m) = \frac{C_m \int_t^{t_m} u_s(t) dt}{t_m} \quad (5)$$

where $u_s(t)$ is the systemability intensity function:

$$u_s(t) = \frac{\alpha * \lambda * \gamma * t^{\gamma-1}}{\beta + \lambda * t^{\gamma}} \quad (6)$$

For $t = 0$, and replacing u_s , $MEC_{\alpha, \beta}(t_m)$, assumes the following form:

$$MEC_{\alpha,\beta}(t_m) = \frac{C_m \left[\alpha * \ln \left(1 + \frac{\lambda}{\beta} * t_m \gamma \right) \right]}{t_m} \quad (7)$$

As calculated by Sgarbossa et al., the optimal time for maintenance is given by

$$t_m^* = \sqrt[\gamma]{\frac{\beta * (\gamma - 1)}{\lambda}} \quad (8)$$

Thus, knowing the optimal time for maintenance and the expected cost of each minimal repair, considering the effect of age and usage thanks to the system-ability model, we can count how many t_m^* are contained in each lease period t . With this, we assume that for each lease period, the parameters change and need to be recalculated:

$$C_m(t) = \frac{t}{t_m} * MEC_{\alpha,\beta}(t_m) \quad (9)$$

After CS and RS have been defined, it can be deduced that the leasing option is convenient compared to purchasing for positive values, not convenient for negative values, and the same convenience if equal to zero.

4.3 Environmental Impact (EI)

The environmental impact (EI) of a product may act, in the form of environmental economics [33], on the selection of a convenience path across sustainability. It can be expressed, in a global approach, as the aggregation of the impacts of its life cycle stages: procurement of raw materials or components (EI_P), manufacturing (EI_M), usage (EI_U) and EOL management (EI_{EOL}).

$$EI = EI_P + EI_M + EI_U + EI_{EOL} \quad (10)$$

Numerous metrics have been developed for measuring environmental impact. In this work, we adopt the global warming potential (GWP), expressed for each phase of the life cycle in carbon dioxide equivalents (kgCO_2e) [29].

$$EI_P = \sum_{w=1}^W M_w GWP_w \quad (11)$$

$$EI_M = \sum_{y=1}^Y GWP_y \quad (12)$$

$$EI_U(u_s, T) = GWP_U(u_s(T)) \quad (13)$$

$$EI_{EOL}(u_s, T) = GWP_{EOL}(u_s(T)) \quad (14)$$

Therefore, Eq. (10) becomes:

$$EI(u_s, T) = \sum_{w=1}^W M_w GWP_w + \sum_{y=1}^Y GWP_y + GWP_U(u_s(T)) + GWP_{EOL}(u_s(T)) \quad (15)$$

In the case of multiple use cycles with EOL recovery (hypothesis of remanufacturing), the EI formulation changes to EI^{uc} . In the latter, the EI_M contribution is integrated in EI_{EOL} . In other words, the impact of end-of-life management in that case corresponds to the impact of reverse logistics and remanufacturing stages, with variable intensity depending on the state of degradation (systemability $-u_s$). Therefore, (15) becomes:

$$EI^{uc}(u_s, T) = \sum_{w=1}^W M_w GWP_w + GWP_U(u_s(T)) + \sum_{y=1}^Y GWP_y(u_s(T)). \quad (16)$$

5 Conclusion

The current political-economic context is reacting to the call for sustainability. The potential of leasing for sustainable circularity can be captured in the proposed remanu-leasing model. This aims to maximise the interests of supply chain agents—(re)manufacturer and consumer—while reducing environmental impact.

The investigation of convenience across circularity paths moves towards the stressors effects. The main idea of the proposed approach is to quantify in advance (while considering the uncertainty of factors affecting systems over time) the consumer effort (in Fig. 1 there is a sketched frame) to gain positive results. A further analysis is then required while considering the remanufacturer alternatives in order to select the best convenience surplus across the two main agents.

This work represents an introduction to the remanu-leasing approach, which will be expanded as a Bees Algorithm (BA) application fixing the optimisation problem. The BA may act while selecting the part and components for remanu-leasing alternative configurations based on the actual usage intensity, environmental-aging stressors, environmental impact of the entire life cycle, and minimal repair actions to service level during the leasing period. The main goal is to balance the CLSC agents' interests while minimising impact, thus selecting the best configuration of the leasing agreement. The exploration of domain of solutions has to be conceived in order to gain (over time) the minimisation of EI^{uc} while respecting the flow value maximisation in CS and RS Consistency is demonstrating with application in real-case automotive instances.

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Life Cycle Costing of Food Technologies: A Case Study of a Milling Plant



Giorgia Casella , Laura Monferdini , Barbara Bigliardi ,
and Eleonora Bottani 

Abstract Life cycle costing (LCC) is a method of assessing the total cost of ownership of a durable item and has been used around the world for the last few decades. This paper investigates the issue of LCC of food technologies, and in particular of a milling plant. The main cost components of this plant are initial acquisition costs, operating costs, maintenance costs and end-of-life costs. An analytic model is developed under Microsoft Excel™ to quantify these cost components. The application of the model is then detailed for one component (i.e., the operating cost) taken as an example, while for the remaining components, we present the main results obtained from the LCC application but omit the detailed computational procedure, for brevity. Overall, outcomes show that the highest economic impact is due to the operating costs, while the remaining costs contributes to the LCC to a limited extent.

Keywords Life Cycle Costing (LCC) · Food industry · Milling plant · Case study

1 Introduction

The history of Life Cycle Costing (LCC) can be traced back to the mid-1960s, where the US Department of Defense applied this technique in its procurement process. In the mid-1980s, attempts were made to adapt LCC to building investments. Over the

G. Casella · L. Monferdini · B. Bigliardi · E. Bottani (✉)
Department of Engineering and Architecture, University of Parma, Viale delle Scienze 181/A,
43124 Parma, Italy
e-mail: eleonora.bottani@unipr.it

G. Casella
e-mail: giorgia.casella@unipr.it

L. Monferdini
e-mail: laura.monferdini@unipr.it

B. Bigliardi
e-mail: barbara.bigliardi@unipr.it

years, the application of LCC has expanded to many areas such as product design, buildings, transportation, and technologies [1].

Even though LCC has been standardized in the building sector by ISO 15686-5, no uniform definition and general standard has been developed yet. The method is favorable as not only purchase prices are taken into account, but a long-term approach is applied, considering cost components over the entire life cycle of the item. Terms such as through-life costing (TLC), whole-life costing (WLC) or total cost of ownership (TCO) are often used synonymously with LCC [2].

The objectives of LCC identified by the Royal Institute of Chartered Surveyors are: (i) to enable investment options to be more effectively evaluated; (ii) to consider the impact of all costs rather than only initial capital costs; (iii) to assist in the effective management of completed buildings and projects; (iv) to facilitate decision-making between competing alternatives [3]. In addition, in today's sustainability-oriented industrial landscape, LCC analysis plays a crucial role in optimizing resources and evaluating the opportunity for remanufacturing, a process that often escapes attention but can result in significant economic and ecological benefits.

In this context, this paper aims to assess the economic feasibility of an investment in a milling plant by integrating LCC methodology. To be more precise, we illustrate the evaluation of the total cost of a stainless steel roller mill by means of an analytic model developed under Microsoft Excel™. The model takes into account the key cost components of manufacturing and using the milling plant throughout its life cycle, although, for the sake of brevity, the details of the computational procedure and its application are provided for a reference cost component only (i.e., the operating cost).

The paper is organized as follows: Sect. 2 illustrates the context from which this work originates. Section 3 describes the LCC implementation for the milling plant and details the application of the model. In Sect. 4, the main results obtained are presented. Discussion, implications, limitations and future research directions are proposed in Sect. 5.

2 Context

This paper focuses on a milling plant manufactured by a company operating in the North of Italy. The company is specialized in the supply of wheat and corn milling plants, feed mills and cereal processing systems. The application of the LCC method to an industrial machine of the company forms the main body of this study. Specifically, an analysis was made for the total cost that the roller mill generates over its entire useful life. Figure 1 shows the roller mill under investigation. The main characteristics of this equipment are:

- Renewed design and dedicated attention to details and hygiene, starting from the careful choice of materials (stainless steel, cast iron and composite materials)
- Fixed on the base there is the grinding rolls assembly

Fig. 1 Stainless steel
rollermill



- The traditional grinding rolls belt transmission is still a milestone achievement and adopted in the rolls assembly, as well as the pneumatic cylinder which engages and disengages the rolls and the micrometric adjustment system
- A set of bearing fixed on rolling guides allows the lift and complete extraction of the grinding rolls assembly, which can be directly placed on a roll carrying trolley
- The feeding group is another self-supporting module easily assembled and disassembled
- The polycarbonate feed tube has a large capacity and the corners are designed to allow a smooth flow of the stock thus avoiding “bridging” and unsanitary accumulation on the walls
- Revolutions electronic control
- Electrical safety—easy installation

In this study, the RMX 125 model, equipped with ridged rollers of diameter 250 mm and length 1250 mm, and with single bell for the incoming product, was analyzed. Technical data about this product are shown in Table 1.

Table 1 Technical information

Model	Dimensions (mm)			Roll dimensions (mm)		Maximum capacity (t/h)
	A	B	C	ø	Length	
RMX 125	2130	1650	1330	250	1250	10.0
				300	1250	10.0
Model	Maximum installed power (kW)			Net weight (kg)		Shipping volume (m³)
	Motor		Gear motor			
	50 Hz	60 Hz				
RMX 125	45	45	0.55	3580	6.5	
				4180		

The life cycle of this type of machine is very long (at least 30 or 45 years), except for exceptional situations.

3 Life Cycle Costing Implementation

To carry out the LCC analysis, four macro-categories of cost were considered, namely initial acquisition cost, operating cost, maintenance cost and end-of-life cost. The cost components were either obtained from quotations, estimated on the basis of the use and maintenance manual of the stainless steel rollermill or derived by applying a specific computational procedure. Microsoft ExcelTM was used for LCC calculation and modelling. The cost computation is explained below. For the sake of brevity, the details of the computational procedure and its application are provided for the operating costs, while for the remaining cost components, we will present the results obtained from the application of the model, omitting the detailed steps.

3.1 *Elements of Life Cycle Costing*

The LCC approach identifies all future costs and benefits and reduces them to their present value by use of the discounting techniques through which the economic worth of a project or series of project options can be assessed. In order to achieve these objectives, the following elements of LCC have been identified:

- Initial acquisition cost: it includes purchasing cost, acquisition cost, installation, commissioning and training cost.
- Operating cost: it includes direct/indirect labour, direct/indirect materials, direct expenses and establishment costs.
- Maintenance cost: it includes direct labour, materials, fuel power, equipment and purchased services.
- End-of-life cost: incurred at the end of an asset's useful life, when disposing of the asset [4].

The numerical values of the input data for all cost components have been obtained from both a data collection phase (interviews), various quotations, and a careful bibliographic analysis carried out with the support of the Scopus database (www.scopus.com).

3.2 *LCC Analysis*

In this section, we describe the application of the computational model to a reference cost component, i.e., the operating cost, taken as a case study. The notation and the

full list of input data used in the analysis (limited to the cost component considered) is shown in Table 2.

Operating costs (OC) are computed on the basis of the following contributions: cost of operating electricity (E), cost of lubricants (L_i), staff salaries (S), cleaning and sanitization (CS), and staff safety (SS_i).

The total cost of electricity can be calculated as follows:

$$E = D_y * H_d * \%ep * Ep * UC_e \quad (1)$$

(Acronyms and their meaning are shown in Table 2). The cost of lubricants varies according to the year under consideration. In particular, the cost associated with the first year (Eq. 2) includes a double dose of engine oil, and grease. Every four years (Eq. 4), in addition to engine oil and lubricant, motor oil must be used.

$$L_{i=1} = Eng_{oil} * UC_{engoil} * 2 + UC_{lubricant} * lubricant \quad (2)$$

$$L_{i=2,3,5,6,7,9,10,11,13,14,15} = Eng_{oil} * UC_{engoil} + UC_{lubricant} * lubricant \quad (3)$$

$$L_{i=4,8,12} = Eng_{oil} * UC_{engoil} + UC_{lubricant} * lubricant + Motor_{oil} * UC_{motoroil} \quad (4)$$

Another operating cost component is the cost of employees who carry out the activities on the machine (i.e., two millers, one mechanic and one electrician). Taking into account the difference in the monthly salary, the following equation can be used:

$$S = (Staff_{mill3A} * UC_{mill3A} * N_{salaries,mill} + Staff_{mill3} * UC_{mill3} * N_{salaries,mill} + Staff_{mecc} * UC_{mecc} * N_{salaries} + Staff_{elect} * UC_{elect} * N_{salaries}) / N_{rollingmill} \quad (5)$$

Assuming that the machine will work for 6 days per week and that a milling plant consists of 20 rolling mills, the cost for cleaning and sanitizing can be calculated as follows:

$$CS = (Disinfectant * UC_{dis} + H_{clean} * D_y / 6 * UC_{clean}) / N_{rollingmill} \quad (6)$$

The cost of staff safety includes two main components: safety shoes and gloves. Shoes are changed every two years, including those of the maintenance employee. Gloves are instead used by three employees (2 mechanics and 1 electrician) and must be substituted 4 times in a year. The following equations can be used for computing the relating costs:

$$SS_{i=1,3,5,7,9,11,13,15} = (UC_{shoe} * (Staff_{mill3A} + Staff_{mill3} + Staff_{mecc} + Staff_{elect} + Staff_{mecc,maint}))$$

Table 2 Nomenclature and input data for the operating costs

Symbol	Description	Unit of measurement	Value	Source
D_y	Working days per year	(days/year)	300	Company
H_d	Working hours	(h/day)	24	Company
$i = 1, \dots, 15$	Years of operation	–	–	–
$\%ep$	Average operation electric power	(%)	78.5	Company
E_p	Electric power	(kW)	44	Company
UC_e	Electric unitary cost	(€/kW)	0.189	[5]
UC_{engoil}	Engine oil unitary cost	(€/liter)	210	[6]
$UC_{lubricant}$	Lubricant unitary cost	(€/kg)	5.555	[6]
Lubricant	Amount of lubricant per year	(kg/year)	10	Company
$Engoil$	Amount of engine oil per year	(liter/year)	0.108	Company
$Motor_{Oil}$	Amount of motor oil per 4 years	(liter/4 years)	3.2	Company
$UC_{motoroil}$	Motor oil unitary cost	(€/liter)	8.50	[6]
$Staff_{mill3A}$	Number of millers with level 3A	–	2	Company
$Staff_{mill3}$	Number of millers with level 3	–	1	Company
$Staff_{mecc}$	Number of mechanics	–	1	Company
$Staff_{elect}$	Number of electrician	–	1	Company
UC_{mill3A}	Monthly cost of millers with level 3A	(€/month)	2721.75	[7]
UC_{mill3}	Monthly cost of millers with level 3	(€/month)	2517.27	[7]
UC_{mecc}	Monthly cost of mechanics	(€/month)	2993.75	[7]
UC_{elect}	Monthly cost of electrician	(€/month)	2541.85	[7]
$N_{salaries,mill}$	Numbers of salaries of millers with level 3A and miller with level 3	–	14	[7]
$N_{salaries}$	Numbers of salaries of mechanics and electrician	–	13	[7]
$N_{rollingmill}$	Number of rolling mills	–	20	Company
Disinfectant	Kilograms of disinfectant per year	(kg/year)	2	Company
UC_{dis}	Disinfectant unitary cost	(€/kg)	17	[8]
H_{clean}	Cleaning hours per week	(h/week)	5	Company
UC_{clean}	Cleaning unitary cost	(€/h)	17	Company
$Staff_{mecc,maint}$	Number of mechanics for maintenance	–	1	Company
UC_{shoe}	Safety shoe unitary cost	(€/safety shoe)	60	[9]
UC_{glove}	Glove unitary cost	(€/glove)	2.5	Company

$$+ UC_{\text{glove}} * (\text{Staff}_{\text{mecc}} + \text{Staff}_{\text{mecc,maint}} + \text{Staff}_{\text{elect}}) * 4) / N_{\text{rollingmill}} \quad (7)$$

$$SS_{i=2,4,6,8,10,12,14}$$

$$= UC_{\text{glove}} * (\text{Staff}_{\text{mecc}} + \text{Staff}_{\text{mecc,maint}} + \text{Staff}_{\text{elect}}) * 4) / N_{\text{rollingmill}} \quad (8)$$

Total operating costs can finally be computed by adding up the contributions listed above:

$$OC = E + \sum L_i + S + CS + \sum SS_i \quad (9)$$

4 Life Cycle Costing Results

By applying the computational procedure described in the previous section together with those of the other cost components (for brevity, only the results are presented), the model returns the results show in Table 3 and Fig. 2, over a 15-year time horizon.

As can be seen from Fig. 2, the cost component with the highest impact is the operating costs (85.87%). Maintenance and initial acquisition costs account for about 7% each. The total cost of end-of-life is almost null (0.13%).

In line with the results shown in the figure above, we now report the main outcomes of the LCC for the share of operating costs.

As shown in Fig. 3, the most onerous component of the operating cost is the electricity (83.23%), followed by the staff salaries (16.22%). For electricity costs, the company could focus future R&D activities on designing energy-efficient equipment or on strategies to reduce the impact of electricity costs on the overall lifecycle costs, for example a solar power system. From a practical point of view, a preliminary (and useful) activity could be a sensitivity analysis conducted with the aim to evaluate the extent to which future changes in energy costs might affect the results of the present LCC analysis. This would demonstrate greater awareness of market dynamics and adaptation of business strategies accordingly. A next step in assessing the overall sustainability of industrial equipment and processes could be the integration of LCC analysis with life cycle assessment (LCA) analysis.

5 Conclusions

This paper has proposed an LCC analysis of food technologies, and in particular of a milling plant. To carry out the analysis, four cost macro-categories were considered, namely initial acquisition costs, operating costs, maintenance costs and end-of-life costs. An analytic model was developed under Microsoft Excel™ to quantify this cost component. The application of the model was detailed for a cost component taken as

Table 3 Life cycle costing of the milling plant

	Description	Lifetime (years)															Total	
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14		15
Initial acquisition costs	Purchase	60,192.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	60,192.00
	Transport	1,150.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1,150.00
	Installation	920.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	920.00
	Electrical testing	400.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	400.00
	Functional testing	240.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	240.00
	Training	95.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	95.00
	Total	62,997.00	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	62,997.00
	Description	Lifetime (years)																
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14		15
Operating costs	Electricity	–	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77
	Lubricants	–	100.92	78.24	78.24	78.24	78.24	78.24	105.44	105.44	78.24	78.24	78.24	78.24	78.24	78.24	78.24	105.44
	Cleaning and sanitization		214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20
	Staff salaries	–	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68

(continued)

Table 3 (continued)

	Description	Lifetime (years)								
		0	1	2	3	4	5	6	7	8
	Staff safety	–	–	19.50	1.50	19.50	1.50	19.50	1.50	19.50
	Total	–	56,557.06	56,516.38	56,534.38	56,543.58	56,534.38	56,516.38	56,534.38	56,543.58
	Description	Lifetime (years)								Total
		9	10	11	12	13	14	15		
Operating costs	Electricity	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	47,051.77	705,776.54
	Lubricants	78.24	78.24	78.24	78.24	105.44	78.24	78.24	78.24	1,277.81
	Cleaning and sanitization	214.20	214.20	214.20	214.20	214.20	214.20	214.20	214.20	3,213.00
	Staff salaries	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	9,170.68	137,560.19
	Staff safety	19.50	1.50	19.50	1.50	1.50	19.50	1.50	19.50	166.50
	Total	56,534.38	56,516.38	56,534.38	56,543.58	56,534.38	56,534.38	56,516.38	56,534.38	847,944.04
	Description	Lifetime (years)								
		0	1	2	3	4	5	6	7	8
Maintenance costs	Preventive	–	–	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94
	Unplanned	–	–	–	–	–	–	132.60	–	2,534.91
	Planned	–	8,214.56	1,564.00	1,564.00	1,564.00	1,564.00	2,039.44	1,564.00	1,564.00
	Total	–	10,160.50	3,509.94	3,509.94	3,509.94	3,509.94	4,117.98	3,509.94	6,044.85

(continued)

Table 3 (continued)

	Description	Lifetime (years)										Total
		9	10	11	12	13	14	15				
Maintenance costs	Preventive	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	1,945.94	29,189.06	
	Unplanned	1,705.50	4,268.58	2,023.50	409.80	–	2,534.91	–	–	15,009.36		
	Planned	1,564.00	2,039.44	1,564.00	1,564.00	1,564.00	1,564.00	1,564.00	1,564.00	31,061.44		
	Total	5,215.44	8,253.96	5,533.44	3,919.74	3,509.94	6,044.85	3,509.94	3,509.94	75,259.86		
End-of-life costs	Description	Lifetime (years)										
		0	1	2	3	4	5	6	7	8		
	Disassembly	–	–	–	–	–	–	–	–	–		
	Transport	–	–	–	–	–	–	–	–	–		
	Total	–	–	–	–	–	–	–	–	–		
	Residual value	–	–	–	–	–	–	–	–	–		
	Total cost	62,997.00	66,717.56	60,026.32	60,044.32	60,053.52	60,652.36	60,026.32	62,579.23	61,453.08		
End-of-life costs	Discounted cost	62,997.00	66,083.16	58,890.20	58,347.72	57,801.77	57,823.05	56,682.07	58,530.85	56,931.02		
	Description	Lifetime (years)										
		9	10	11	12	13	14	15	Total			
	Disassembly	–	–	–	–	–	–	920.00	920.00	920.00		
	Transport	–	–	–	–	–	–	408.00	408.00	408.00		
	Total	–	–	–	–	–	–	1,328.00	1,328.00	1,328.00		
End-of-life costs	Residual value	–	–	–	–	–	–	–9,028.80	–9,028.80	–9,028.80		
	Total cost	61,749.82	64,770.34	62,067.82	60,463.32	60,044.32	62,561.23	52,343.52	978,550.10	978,550.10		
	Discounted cost	56,661.96	58,868.47	55,875.80	55,913.79	53,031.08	54,728.62	45,354.75	912,521.33	912,521.33		

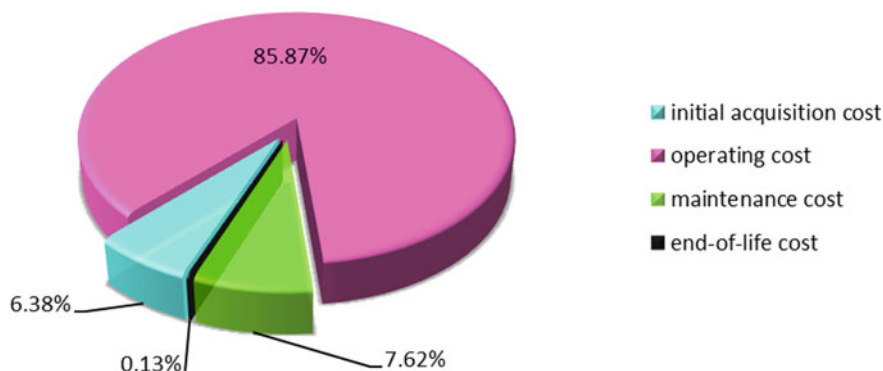


Fig. 2 Share of the cost components on the total cost

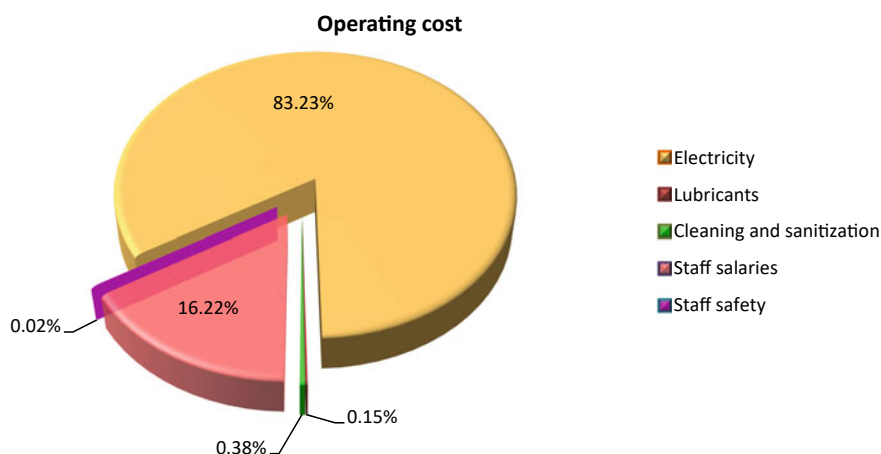


Fig. 3 Share of the cost components—details for the operating costs

an example (i.e., the operating cost), while for the remaining macro-categories, the detailed computational procedure is omitted, for brevity, and only the main results are presented.

We found that the highest economic impact of LCC is due to the operating costs, while the remaining macro-categories contribute to the LCC to a limited extent. In particular, the purchasing cost of the rolling mill represents only about 6% of the total expenditure that it will generate during a life cycle of 15 years. Moreover, the most onerous operating cost component is the electricity, followed by the staff salaries. By the way, this result reflects the fact that in Italy, the cost of electricity has significantly risen (approximately tripled) since the end of 2021 [10], while the equipment under examination is likely to have been designed and manufactured before that date; thus, the cost of electricity was probably expected to be lower. At

the same time, the fluctuation in the cost of energy could take an opposite direction in the next years, and therefore, it would be useful to repeat the analysis in some years, to check whether the trends in the cost of electricity have changed and to what extent the results are sensitive to such a cost. More in general, it would also be appropriate to suggest the company to design new equipment with a focus on energy saving devices or strategies, in an effort to reduce the impact of the electricity cost on the total LCC.

Further developments will be the sensitivity analysis of the results by varying the years of service life, which means assuming, for example, 30 and 45 years according to the long life cycle of this type of machine. Moreover, the quantification of environmental sustainability by integrating LCC analysis with LCA could be added. Given the importance of circular economy (CE) and remanufacturing, combined CE-LCC logics could also be applied. These logics are based on the existing LCC techniques and adapted to meet the requirements of CE products [11]. In addition, it is crucial to consider how the LCC approach can be applied in remanufacturing contexts. The adoption of LCC in these situations can provide a clear and comprehensive view of costs throughout the life cycle of products or equipment undergoing remanufacturing. Once again, LCC analysis can be used to evaluate different design alternatives in a remanufacturing context [12] and can help identify the most relevant cost components, such as operating costs, that can significantly affect remanufacturing decisions. In addition, LCC analysis can help evaluate the effectiveness of remanufacturing practices in reducing total costs in the long run, as well as considering environmental and sustainability aspects.

In conclusion, the LCC analyses developed help both the company and potential customers. Indeed, the case analyzed shows that the purchase price is an almost negligible cost compared to the total charges generated during the entire useful life.

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A Model for Remanufacturing Process Planning Under Quality Loss and Emissions Constraint with Multi-graded of Incoming Cores



Mohamad Imron Mustajib , Udisubakti Ciptomulyono ,
and Nani Kurniati

Abstract Remanufacturing plays an important role to contribute for circular economy by extending the life cycle of used products. Remanufacturing is a recovery process of worn-out product through multi-process remanufacturing to achieve quality, specifications, and performance “as good as new” condition. It Remanufacturing processes focuses on disassembling, cleaning, repairing, and reassembling used products or components to restore them to like-new or even better-than-new condition. The basic problem in a remanufacturing process planning is how to appropriately select the manufacturing/remanufacturing process (technology) to have in a remanufacturing company that has the capability to ensure “like new” quality of remanufactured product. This paper presents a mathematical model for optimizing remanufacturing processes planning by considering quality loss and carbon emissions. The model was formulated using integer linear programming to obtain optimal solution. We study a remanufacturing system with four stage processes under varying quality condition of incoming core. This study also considered multiple remanufacturing processes that can be selected for each stage of the processes, then the processes may lead to different process characteristics, i.e. quality tolerance and carbon emission. A numerical example was used to validate the proposed model for a case of remanufactured hydraulic cylinder process planning. The model consistently shows an optimal solution for the case.

Keywords Optimization · Remanufacturing planning · Quality grade · Tolerance · Emission

M. I. Mustajib (✉)
Universitas Trunojoyo Madura, Bangkalan 69162, Indonesia
e-mail: imronmustajib@trunojoyo.ac.id

U. Ciptomulyono · N. Kurniati
Institut Teknologi Sepuluh Nopember, Surabaya 60111, Indonesia

1 Introduction

Remanufacturing is a critical component of establishing a circular economy. In the circular economy which aims to obtain economic and environmental advantages by recovery the residual value of used products [1], remanufacturing has become an important strategy for realizing a successful a closed loop production system. This was due to the closed loop production system, a used product in the phase of end of life (EoL) can be salvaged by using recovery processes into remanufactured products that have an added value. Remanufacturing is better than recycling of them as for three main reasons: less need to consume raw energy, it was still retained its original shape, and the quality of remanufactured products is as good as new. For these reasons, valuable used products and resources can be maintained in circulation for multi periods of time.

Remanufacturing process optimization is a critical issue to be addressed for several important reasons for addressing environmental, economic, and social challenges. It promotes sustainability, conserves resources, and provides economic benefits, making it an important focus for businesses, policymakers, and society as a whole. An efficient remanufacturing process planning is essential for organizations looking to optimize their operations, reduce costs, improve quality, and remain competitive in today's dynamic business environment.

In order to recover worn-out products which are restored to as good as new condition, remanufacturing system requires many operation activities (processes). The remanufacturing processes of used product (core) are more complex than first manufacturing processes due to the quality uncertainties from unknown conditions of technological and physical of used product. General processes in remanufacturing operation includes: quality inspection of incoming core, core disassembly, cleaning process, reprocessing/reconditioning, reassembly, and final performance testing of remanufactured product.

The main challenges faced by remanufacturing company are dealing with the supply side of material and demand side of customer preferences. From the supply side, remanufacturer was faced by the problem of uncertainties on quality, quantity, and arrival time of incoming core (used products) which are acquired from end users or collectors. After that, from demand side, the customers tend to select remanufactured products depending on their preferences based on price, quality level, and environmental consideration [2]. Hence, one of the crucial issue for balancing supply and demand in remanufacturing system is how to control the quality of remanufacturing process to assure that the quality level of remanufactured products is not worse than its original specification of product design (as good as new). This is due to they came from used products (incoming core) with varying quality condition. In terms of quality-based strategies, the company focuses on satisfying customer needs by integrating quality into all stages of the related process in the system. Therefore, managing quality uncertainty of used product is an important issue in remanufacturing systems. This uncertainty, if unmanaged correctly, could lead to high cost of quality and remanufacturing operations. A High-quality of used product need few

reprocessing (lower remanufacturing cost), while a lower-quality of used product would necessitate extensive reprocessing (higher remanufacturing cost). The problem of remanufactured products' quality has an impact on dissatisfaction customer needs, due to used parts may be not processed correctly was also identified by Wang et al. [3].

Remanufacturing process planning contributes a major part of remanufacturing operations activity, due to the processes of bridging between used products and remanufactured products. The first step in remanufacturing process planning is concerned with the key quality characteristics analysis of used product to determine the important part that should be reconditioned. This activity is employed as the identification of parts and its tolerances. After that, it is important to determine the appropriate types of reconditioning operations (process selection). Based on the desired accuracy and precision, this can be varying. To complete any of the processes required in remanufacturing system for converting used product into a high quality remanufactured product for satisfying the customer needs as good as original design requirements and considering technological and resource constraints, remanufacturing company needs to develop an efficient process planning. Therefore, process planning plays an important role in remanufacturing system, since it affects cost saving capability in terms of remanufacturing cost and achieving in remanufactured product quality.

It is now well established from a variety of definitions [4–6] that process selection is known as the strategic decision of choosing which kinds of manufacturing processes or technology that are available and feasible to produce its product to have in the plant. Numerous studies have attempted to review critical issue in remanufacturing process planning [7] and taxonomy remanufacturing processes [8]. In the real process, one part can be normally produced by several appropriate process technologies, but every process exhibits significant differences in process characteristics and each process has its own attribute [9]. However, for each process, the considerations taken should not only be based on economic considerations (production costs, production rate), but also technical considerations (forms can be produced, process variations, dimensional constraints and tolerances, accuracy, and surface quality) and environmental considerations (carbon emissions, pollution, resource consumption).

2 Literature Review

Several studies on the remanufacturing process planning and its decision have been proposed in many literatures. Jiang et al. [10] recommended a multiple criteria decision making approach for choosing remanufacturing technology portfolio by employing six major criteria: cost, time, quality, environmental impact, service, and

resource consumption. Moreover, Jiang et al. [11] constructed a model for determining optimal remanufacturing process plan selection by combining quality function deployment (QFD) and fuzzy linear regression to find the functional relationships between remanufacturing objective and process quality characteristics. Meanwhile, Zhang et al. [12] explored the problem of remanufacturing process route selection by considering manufacturing time, manufacturing quality, manufacturing costs, resources consumption, environmental emissions and engineering characteristics of each remanufacturing process stage are presented into an integrated model based on QFD, fuzzy linear regression and goal programming. Furthermore, Jiang et al. [13] studied the effects of reliability and cost on remanufacturing process planning decision.

To better understand quality uncertainty of incoming core (used product) and its effects to environmental benefits of the remanufacturing system, Liao et al. [14] proposed a mathematical model for the remanufacturing routing selection. Recently, Liao et al. [15] built an assessment model on environmental benefits by considering multiple uncertainties conditions and proposed a non-probabilistic method for determining functional relationship among the quality loss coefficient and different environmental indexes. Meanwhile, Zhou et al. [16] studied the effect of highly quality uncertainty of end life of product on carbon emissions by proposing a model to determine the optimal acquisition and remanufacturing decision of the independent remanufacturing system. Moreover, Liao et al. [17] studied acquisition quantity, quality, and market demand uncertainty, and the relationships to production strategies. On the other hand, a number of authors [18–20] have studied the effects quality uncertainty on quality control of reassembly process. Several lines of evidence suggest that allocation of tolerance dimension as quality level on parts give better quality of final remanufactured product reassembly. Liu et al. [21] proposed a technique of tolerance grading allocation for remanufactured parts is performed based on the uncertainty analysis of the remanufacturing assembly. Furthermore, Liu [19] recommended a technique of tolerance grading allocation for the tolerance redistribution optimization model of the reassembly dimensional chain to ensure the uncertainty of reassembly is not lower than the assembly. Dimensional tolerances are also selected to make a trade-off between quality requirements and manufacturing costs which is typically judging how much variation is allowed in the product while still maintaining in the quality specification for the product or brand [22, 23]. Dimensional tolerances in a reconditioned part is the allowance of the part layer to be removed from the surface of a used part in remanufacturing processes to eliminate dirt and surface damage. Therefore, required accuracy and surface quality could be achieved. Tolerance allocation affects environmental impacts through reconditioning processes as well as the amount of resource consumption and discarded parts. Even though by allocating tight tolerance will improve the quality of reconditioned part, the machining cost will also increase. Consequently, this increases the remanufacturing cost, more resource-intensive processes, and emissions. On the other hand, by allocating loss tolerance, it will reduce cost, but it also often increases inappropriate in the reassembly capability and functionality of remanufactured product. Therefore, this increases the discarded parts (scrap for material recovery).

Together, these previous studies indicate that remanufacturing and quality cost (economic factor), dimensional constraints and tolerances (technical factor), and carbon emissions (environmental factor) are important considerations that should be taken in remanufacturing process planning. Dimension constraints and tolerance are the main determinant factors not only for supplier selection [24], but also for process selection and (re)assembly ability [25–28] for quality assembled products. In addition, it has been suggested that three types of environmental legislation can be applied in selection of product and manufacturing processes; penalties (taxes), thresholds values (allowed value), and trading of output allowances [29, 30]. However, there remains a need for an efficient method that can find optimal solution for remanufacturing process selection with varying quality condition of incoming core by considering remanufacturing and quality cost, dimensional constraints and tolerances, and emissions factor. In the present study, we developed a mathematical model for optimizing remanufacturing processes planning with varying quality condition grade of incoming core under consideration of remanufacturing and quality cost, dimensional constraints and tolerances, and carbon emissions factor.

The rest of the paper is organized as follows: Sect. 3 defines the used notation in the proposed model and describes the system under the study. Section 4 presents the mathematical model formulation. Section 5 provides a numerical example for a case study. Section 6 concludes the results of the study and provides suggestions for potential further research.

3 Notation and System Description

We first define the notations that are used in the system description and for formulating the problem by using a mathematical model.

3.1 Notations

The following notations are used in this study to express the proposed model.

i. Indices:

i	:	i -th part, $i = 1, 2, \dots, I$
j	:	j -th grade of core quality condition, $j = 1, 2, \dots, J$
k	:	k -th <i>stage</i> of process, $k = 1, 2, \dots, K$
l	:	l -th process alternative, $l = 1, 2, \dots, L$
m	:	m -th type of emission, $m = 1, 2, \dots, M$
I	:	number of parts
J	:	number of grade of core quality condition

K	:	number of stages
L	:	number of processes alternatives
N	:	number of emissions subject to emission taxes and/or threshold values ($N \leq M$)
M	:	total number of emission types

ii. Performance:

TC	:	Total of Cost

iii. Parameters:

A, B	:	constant of function of cost tolerance
y	:	critical-to-quality (CTQ) characteristic of assembled (remanufactured) product $y = (x_1, \dots, x_i, \dots, x_I)$
x_i	:	individual quality characteristic of parts, such as the dimension of i -th part
$\frac{\partial y}{\partial x_i}$	:	partial derivative of CTQ with respect to i -th part, which reflects dependency of the functional dimension (y) on individual quality characteristic of parts at i -th part (x_i)
σ_{kl}^2	:	variance dimension at k -th stage for the l -th process alternative
σ_{ijkl}^2	:	variance dimension of i -th part at j -th grade of core quality condition at k -th stage for the l -th process alternative
USL_{ijkl}	:	upper specification limit of l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
LSL_{ijkl}	:	upper specification limit of l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
Cp_{ijkl}	:	process capability index of l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
μ_{ijk}	:	process mean of l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
τ_{ijkl}	:	process target of l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
t_{ijkl}	:	tolerance for l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
t_y	:	design tolerance or customer specification of final assembled product
Q_m	:	unit penalty for m -th type of emission ($m = 1, 2, \dots, M$)
Q_m^+	:	unit purchase price for m -th type of emission, if m is dependent on trading allowances
Q_m^-	:	unit selling price for m -th type of emission, if m is subject dependent on allowances ($Q_m^- \leq Q_m^+$)
ε_{ijklm}	:	amount of m -th emission per unit remanufactured product for l -th process at the k -th stage for reconditioning process of the i -th part from the j -th grade
e_m	:	amount of m -th type of emission

e_m^+	:	amount of purchased units for m -th type of tradable emission
e_m^-	:	amount of sold units for m -th type of tradable emission
E_m^T	:	allowance unit for m -th type of tradable emission
E_m	:	maximum allowed level for m -th type of emission

iv. Decision variables:

x_{ijkl}	:	$\begin{cases} 1, \text{ if } l\text{-th process at the } k\text{-th stage is selected for reconditioning} \\ \text{process of the } i\text{-th part from the } j\text{-th grade} \\ 0, \text{ if otherwise} \end{cases}$

3.2 System Description

Remanufactured engine, alternator, hydraulic cylinder are the examples to illustrate how remanufacturing processes can be applied to products to provide sustainable, high-quality alternatives while also reducing the overall ecological footprint. It is described in Fig. 1 that the remanufacturing systems in this study are divided into four stages of processes: core acquisition and sorting, disassembly and inspection, remanufacturing process—including cleaning and reconditioning of parts, and reassembly and final testing. First of all, the incoming core are sorted/graded based on their quality condition into 1st quality to J -th grade ($1, \dots, j, \dots, J$), where 1st grade implies the high quality condition, while J indicates lower quality condition. These quality grades differ, for example in preliminary inspection based on usage condition, physical condition, and technological condition criteria of incoming core. Second, each of the cores in j -th grade is disassembled to be I -th part ($1, \dots, i, \dots, I$). After that, the ij -th part is reprocessed/reconditioned in the multistage processes from stage 1 to K -th stage ($1, \dots, k, \dots, K$). Meanwhile, every stage of these processes has a number of alternative processes that can be selected in each k -th stage from processes 1st to L -th process ($1, \dots, l, \dots, L$). Each of l -th process alternative at k -th stage has the characteristics of remanufacturing cost (c), dimensional tolerance quality (t), and carbon emission of process (e) characteristics (c_{kl}, t_{kl}, e_{kl}). Meanwhile, each of ij -th part is reprocessed in kl -th process results quality variance of part (σ_{kl}^2). Finally, in the reassembly and final testing, total quality variance of parts ($\sigma_{1l}^2 + \dots + \sigma_{kl}^2 + \dots + \sigma_{Kl}^2$) should be equal or less than quality specification of final remanufactured assembly product (σ_Y^2). Therefore, the optimal of selected process planning denoted by equation $Y^* = f(X_{1l}^*, X_{kl}^*, X_{Kl}^*)$. In order to ensure final assembly of remanufactured product meet quality specification the original product, then total variance for the i -th part from the j -th grade which is processed in the k -th stage by using selected l -th process, the functional requirement can be expressed by Eq. (1)

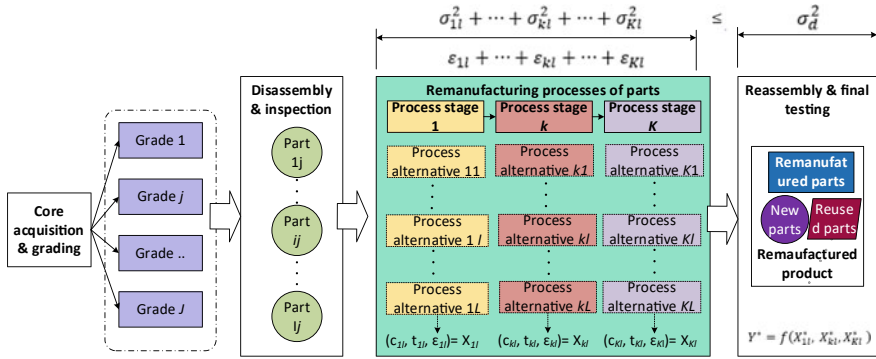


Fig. 1 System description of remanufacturing process planning under study

$$(\sigma_{ij1l}^2 + \dots + \sigma_{ijkl}^2 + \dots + \sigma_{ijKl}^2) \leq \sigma_y \quad (1)$$

In addition, the ability of each process alternative for remanufacturing the used parts that consistently stays within the specification limit can be estimated by the process capability index:

$$Cp_{ijkl} = \frac{USL_{ijkl} - LSL_{ijki}}{6\sigma_{ijkl}} \quad (2)$$

Montgomery [31] emphasized that the index in Eq. 2 indicates that the natural tolerance limits (t) in the process (with 3 sigma above and below the mean) are inside the lower and upper specification limits. Hence, by paying attention to the tolerance limit on one side only, Eq. 2 can be simplified as:

$$Cp_{ijkl} = \frac{t_{ijkl}}{3\sigma_{ijkl}} \quad (3)$$

Therefore, the variance can be stated as:

$$\sigma_{ijkl}^2 = \left(\frac{t_{ijkl}}{3Cp_{ijkl}} \right)^2 \quad (4)$$

Meanwhile, the variable of critical-to-quality (CTQ) characteristics of assembled product (y) can be estimated from the characteristics of each part ($x_1, \dots, x_i, \dots, x_I$). This relationship can be mathematically expressed by Eq. (5):

$$y = f(x_1, \dots, x_i, \dots, x_I) \quad (5)$$

Partial derivative in Eq. (5) shows the quality characteristic sensitivity of the final assembled remanufactured product (y) to the quality characteristics of the i -th part

(x_i) .

$$\sigma_y^2 = \sum_{i=1}^I \left(\frac{\partial y}{\partial x_i} \bigg|_{\tau=x_i} \right)^2 \sigma_i^2 \quad (6)$$

Furthermore, the expected quality loss of the final assembled product (Y) can be done by incorporating Taguchi quadratic loss function, and it can be written in Eq. (7) as the total cost of quality loss (QL_y) of the the i -th part with j -th grade, which is reprocessed at k -th stage by using l -th alternative process:

$$QL_y = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L k_{ijkl} \left(\sigma_{ijkl}^2 + (\mu_{ijk} - \tau_{ijkl})^2 \right) \quad (7)$$

By substituting Eq. (6) into Eq. (7), we find the following total cost of quality loss

$$QL_y = k_y \left(\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \left(\frac{\partial y}{\partial x_i} \bigg|_{\tau=x_i} \right)^2 \left(\frac{t_{ijkl}}{3Cp_{kl}} \right)^2 \right) \quad (8)$$

On the other hand, in this paper, we employ ‘cost-tolerance reciprocal squared model’ [24] to calculate remanufacturing process cost. This process can be either subtractive process to remove the used part material surface, or additive process for depositing part surface.

4 Mathematical Model

The objective function of the developed model is minimizing total cost of remanufacturing process cost, quality loss cost, and emission cost (penalty and trading cost) as expressed by Eq. 9 below. The equations for remanufacturing costs, quality losses and emissions were obtained by some modification from previous basic model. The first term of objective function refers to remanufacturing or reconditioning cost based on cost-tolerance generated process alternative. The second term is quality loss cost based on Taguchi loss function. The third term is emissions penalty cost and taxes based on governments policy. And, the fourth and fifth terms refer to purchase cost of tradable allowance.

$$\begin{aligned} Min TC = & \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \left(A_{ijkl} + \frac{B_{ijkl}}{t_{ijkl}^2} \right) X_{ijkl} \\ & + k_y \left(\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \left(\frac{\partial y}{\partial x_i} \bigg|_{\tau=x_i} \right)^2 \left(\frac{t_{ijkl}}{3Cp_{kl}} \right)^2 \right) X_{ijkl} \end{aligned}$$

$$-\sum_{m=1}^N Q_m e_m + \sum_{m=N+1}^M Q_m^- e_m^- - \sum_{m=N+1}^M Q_m^+ e_m^+ \quad (9)$$

Subject to

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \left(\frac{\partial y}{\partial x_i} \Big|_{\tau=x_i} \right)^2 t_{ijkl}^2 X_{ijkl} \leq t_d^2 \quad (10)$$

$$\sum_{l=1}^L X_{ijkl} = 1, \forall_i \in I, \forall_j \in J, \forall_k \in K \quad (11)$$

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^L \varepsilon_{mijkl} X_{ijkl} = e_m \quad (12)$$

$$e_m \leq E_m \quad (13)$$

$$e_m + e_m^- - e_m^+ = E_m^T \quad (14)$$

$$X_{ijkl} = (0, 1), \forall_i \in I, \forall_j \in J, \forall_k \in K, \forall_l \in L \quad (15)$$

Furthermore, various constraints are expressed by Eqs. 10–15. Equation 10 constitutes a main quality constraint of model, where final remanufactured product quality should meet quality specification of the original product design or as good as new. Therefore, tolerance value of final assembled remanufactured product (t_y) should be less than or the same as tolerance value of its original product quality (t_d). Equation 11 ensures that only one process is selected for each remanufacturing stage. Meanwhile, Eqs. 12–14 are three types of environmental legislation constraints for pollutant emissions that we adapted from Letmathe and Balakrishnan [29]. Total amount of emissions acquired from each emission of the selected process for all remanufacturing stages is expressed by Eq. 12. In addition, threshold of total amount emission is expressed by Eq. 13. Then, Eq. 14 expresses government's policy constraint for the quantity of allowance units for traded emission (E_m^T). Finally, we use binary constraint for the decision variable of remanufacturing process selection by using Eq. 15.

5 Numerical Example

To validate the implementation of proposed model, we present a numerical example in this section that considers the quality characteristics of a remanufactured product—a hydraulic cylinder as a case study. In business practice, many remanufacturing

companies have recovered the used hydraulic cylinder for heavy equipment components (front suspension, rear suspension and hoist cylinders). For example, a leading global remanufacturing company in Indonesia promoted the remanufactured products through its remanufacturing business by extending the life cycle of hydraulic cylinders for mining and construction heavy equipment [32]. The used hydraulic cylinders are acquired from the customer's hand are delivered to remanufacturing plant where they are inspected based on physical condition, usage condition, and technological condition. The main physical damage is found to be some scratches on the surface of cylinder barrel. This damage causes leakage that will reduce the resulted power of the hydraulic cylinder. After the inspection process, they are graded into multiple quality grades. Then, remanufacturing plant engages in multi-stage remanufacturing processes to provide high quality remanufactured hydraulic cylinders to ensure customer satisfaction. Disassembly, cleaning, machining, surface finishing, and reassembly are the most important processes in the hydraulic cylinder remanufacturing. Cleaning plays a critical role in the remanufacturing process of hydraulic cylinder. This is mainly not only caused by requirement of high processing time and resource consumption, but also it also affects the cost of remanufacturing, quality, and carbon emission.

The main performance of remanufactured hydraulic cylinder is an aspect that must be met as good as the original quality specification design. The purpose of hydraulic cylinder design is to provide power through a directional stroke from pressurized hydraulic fluid on both extension and retraction. The hydraulic cylinder consists of main three parts which are reconditioned, i.e. 1. cylinder barrel, 2. piston, 3. piston rod. Meanwhile, the others parts are reused and replaced (seals, ring) by new one. The piston slides in the chamber with seals and rings. This divides the inside of the cylinder into two chambers, the left chamber and the right chamber (piston rod side) as described in Fig. 2.

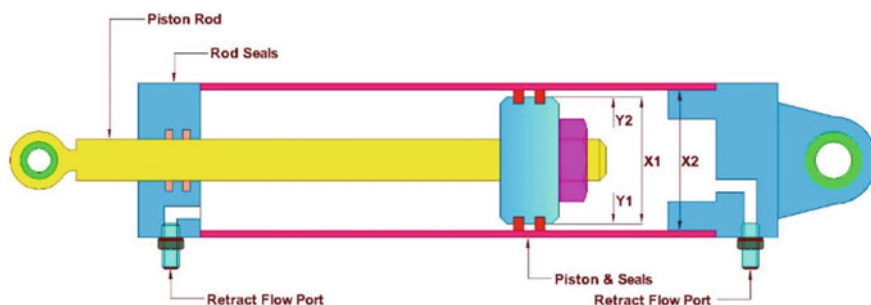


Fig. 2 Remanufactured hydraulic cylinder

5.1 *Quality Characteristics of Product*

The critical to quality (CTQ) characteristics of hydraulic cylinder is determined by its basic principle that employs a piston which slides inside a cylinder barrel to convert flow into linear action and pressure into force. Pascal's law specifies that the force (F) exerted on a surface is equal to the pressure (p) exerted on the surface times the area (A) of the surface. The precision of this area is determined by the critical dimension of the clearances Y_1 and Y_2 between the internal cylinder diameter (X_2) and the piston diameter (X_1) (see Fig. 2). The clearance between the cylinder and piston can causes fluid leakage, which leads to volumetric and mechanical loss that contribute to quality of cylinder hydraulic performance. Mathematically, if $y_1 = y_2$, then we can express the relationship as follows:

$$y = 2y_1 = x_2 - x_1 \quad (16)$$

The Eq. 16 above shows that the dimensional tolerance of cylinder and piston part determines the final CTQ of the hydraulic cylinder. Hence, partial derivative of CTQ that reflects dependency of the functional dimension (y) of hydraulic cylinder on individual quality characteristic of parts at i -th part (x_i) can be obtained by using Eq. 16.

5.2 *Remanufacturing Process Characteristics*

The used hydraulic cylinders acquired from the customer's hand are delivered to remanufacturing plant where they are inspected based on physical condition, usage condition, and technological condition. After that, they are graded into multiple quality grades: from highest quality to lowest quality. In this study, we used two quality grades of incoming core as shown in Table 1. Furthermore, Table 1 provides numerical data of process characteristics for remanufacturing planning at each of stages—including cost for reconditioning, dimensional tolerance, and amount of emission.

5.3 *Optimization*

The solution of the mixed integer linear programming (MILP) model can be obtained easily by using LINGO 11.0 optimization software. The decision variables related to process selection obtained are presented in LINGO 11.0 language output below. The emission amount for the m -th emission type (e_m) is 941.8 kg.CO₂.eq. Meanwhile, values of the variables e_m^- and e_m^+ to represent the number of emission allowances sold and purchased are 4058.2 kg.CO₂.eq. and 0.

Table 1 Process characteristics of remanufacturing planning

Grade (<i>i</i>)	Parts (<i>j</i>)	Stages (<i>k</i>)	Process alternatives (<i>l</i>)		Constants and cost			Tolerance (<i>t_{kl}</i>)	Emission (<i>ε_{kl}</i>)
					<i>A_{kl}</i>	<i>B_{kl}</i>	(<i>c_{kl}</i>)		
1	Cylinder barrel (1)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.596
			2	Immersion cleaning	0.12	0.045	50.12	0.03	0.588
		Machining (2)	1	Grinding	0.34	0.25	100.34	0.05	0.897
			2	Honing	0.35	0.12	192.35	0.025	0.659
			3	Shaping	0.3	0.35	140.30	0.05	0.724
	Piston rod (2)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.436
			2	Immersion cleaning	0.12	0.045	50.12	0.03	0.458
		Machining (2)	1	Milling	0.34	0.25	100.34	0.05	0.789
			2	CNC turning	0.35	0.12	192.35	0.025	0.521
			3	Conventional turning	0.31	0.36	178.09	0.045	0.689
	Piston (3)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.356
			2	Immersion cleaning	0.12	0.045	50.12	0.03	0.378
		Machining (2)	1	Milling	0.34	0.25	100.34	0.05	0.635
			2	CNC turning	0.35	0.12	192.35	0.025	0.451
			3	Conventional turning	0.31	0.36	178.09	0.045	0.565
2	Cylinder barrel (1)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.596
			2	Immersion cleaning	0.12	0.045	50.12	0.03	0.588
		Machining (2)	1	Grinding	0.34	0.25	100.34	0.05	0.897
			2	Honing	0.35	0.12	192.35	0.025	0.659
			3	Shaping	0.3	0.35	140.30	0.05	0.724
	Piston rod (2)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.436
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			2	CNC turning	0.35	0.12	192.35	0.025	0.521
			3	Conventional turning	0.31	0.36	178.09	0.045	0.689
	Piston (3)	Cleaning (1)	1	Shot blasting	0.15	0.05	80.15	0.025	0.356
			2	Immersion cleaning	0.12	0.045	50.12	0.03	0.378

(continued)

Table 1 (continued)

Grade (<i>i</i>)	Parts (<i>j</i>)	Stages (<i>k</i>)	Process alternatives (<i>l</i>)		Constants and cost			Tolerance (<i>t_{kl}</i>)	Emission (<i>ε_{kl}</i>)
					<i>A_{kl}</i>	<i>B_{kl}</i>	(<i>c_{kl}</i>)		
		Machining (2)	1	Milling	0.34	0.25	100.34	0.05	0.635
			2	CNC turning	0.35	0.12	192.35	0.025	0.451
			3	Conventional turning	0.31	0.36	178.09	0.045	0.565

Global optimal solution found.

Objective value: 35,028.43
Objective bound: 35,028.43
Infeasibilities: 0.000000
Extended solver steps: 0
Total solver iterations: 0

Variable	Value	Reduced Cost
X1111	1.000000	2362.250
X1112	0.000000	2504.920
X1121	0.000000	1865.740
X1122	1.000000	1700.150
X1123	0.000000	1815.800
X1211	0.000000	2191.150
X1212	1.000000	2136.620
X1221	1.000000	1723.140
X1222	0.000000	1807.450
X1223	0.000000	2006.780
X1311	1.000000	2022.950
X1312	0.000000	2151.120
X1321	0.000000	1865.740
X1322	1.000000	1700.150
X1323	0.000000	1800.880
X2111	1.000000	4022.550
X2112	0.000000	3109.230
X2121	0.000000	2756.040
X2122	1.000000	2539.750
X2123	0.000000	3148.000
X2211	1.000000	3210.550

X2212	0.000000	3254.230
X2221	0.000000	3026.340
X2222	1.000000	2858.750
X2223	0.000000	3221.020
X2311	0.000000	3790.550
X2312	1.000000	3108.230
X2321	1.000000	2643.340
X2322	0.000000	3003.750
X2323	0.000000	2786.020
E1	941.8000	0.000000
EP	4058.200	0.000000
EM	0.000000	0.000000

Row	Slack or Surplus	Dual Price
1	35,028.43	−1.000000
2	0.5340460	0.000000
3	0.000000	29.00000
4	0.000000	0.000000
5	0.000000	0.000000
6	0.000000	0.000000
7	0.000000	0.000000
8	0.000000	0.000000
9	0.000000	0.000000
10	0.000000	0.000000
11	0.000000	0.000000
12	0.000000	0.000000
13	0.000000	0.000000
14	0.000000	0.000000
15	0.000000	0.000000
16	5058.200	0.000000
17	0.000000	−1.000000

6 Conclusion

The present model was developed to determine the optimal of process selection in remanufacturing planning under quality and emission constraints. This model has shown that the single objective function refers to remanufacturing or reconditioning cost and quality loss cost in linear formulation with single decision variable. This model establishes a quantitative framework for selecting optimal process for reconditioning in remanufacturing system when the incoming cores have quality grade differences. The major limitation of this model is the quality grade of incoming core was predetermined and no disposal part in disassembly process. Considerably, further works will need to be done to determine optimal process planning with multi-objective function. A further study could assess the effects of uncertain quality of incoming cores.

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Science Mapping Analysis for the Development of a Remanufacturing Readiness Model



Saverio Ferraro , Alessandra Cantini , Leonardo Leoni ,
and Filippo De Carlo 

Abstract Nowadays, most industrial processes require increased attention to the rational use of resources in line with economic, environmental, and social principles. In this context, products in a state of deterioration present valid solutions for reintegration into the lifecycle through the use of recovery, restoration, and reuse techniques. The so-called remanufacturing process is a facilitator of sustainability and circular economy practices through the design of closed-loop supply chains. However, transitioning from linear to closed-loop supply chains through the introduction of remanufacturing is not straightforward. For this reason, the aim of this paper is to provide a tool for assessing the readiness level for introducing remanufacturing from a circular economy perspective. A multi-methodological design approach, including a systematic literature review on readiness models and a systematic literature network analysis for remanufacturing adoption, is employed to identify gaps and propose a novel readiness model. The results propose R4CE, a remanufacturing readiness model for circular economy adoption in closed-loop supply chains. The model assesses the readiness on five levels and the three dimensions of collaboration mechanisms, closed-loop supply chain decisions, and policies and regulations. The research findings may be of interest to practitioners and researchers for readiness assessment.

S. Ferraro (✉) · A. Cantini · L. Leoni · F. De Carlo
Department of Industrial Engineering (DIEF), University of Florence, Viale Morgagni, 40, 50134
Florence, Italy
e-mail: saverio.ferraro@unifi.it

A. Cantini
e-mail: alessandra.cantini@unifi.it; alessandra.cantini@polimi.it

L. Leoni
e-mail: leonardo.leoni@unifi.it

F. De Carlo
e-mail: filippo.decarlo@unifi.it

A. Cantini
Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Via
Lambruschini, 20156 Milan, Italy

Keywords Remanufacturing · Circular economy · Closed-loop supply chain · Sustainability · Maturity model

1 Introduction

To deal with increasing resources scarcity and environmental concerns, the concept of circular economy (CE) emerges as a necessary solution. The objectives of CE encompass various practices aimed at fully maximizing the residual value of products and services at the end of their use [1]. While the initial focus was primarily on environmental aspects, the CE paradigm has evolved into a competitive advantage for organizations. In fact, it brings about additional benefits such as energy efficiency, effective waste management, and servitization [2]. Moreover, the adoption of CE practices contributes to the resilience of supply chains by reducing price fluctuations and supply shortages [3]. However, the introduction of CE in companies and supply chains entails not only benefits but also critical challenges. These challenges are of a systematic nature, involving high complexity, inherent risks, and the need for multidisciplinary and interdisciplinary approaches [4]. Furthermore, there is a lack of comprehensive knowledge in this area. As emphasized by Parida et al. [2], despite the well-understood benefits, few practical examples have successfully implemented CE practices. Similarly, Thorley et al. [5] highlight the limited adoption of CE practices among small and medium-sized enterprises.

According to CE, before disposing of a product or service, actors within a value chain have several alternatives to consider, such as reuse, repair, refurbishing, recycling, and remanufacturing. Among these processes, remanufacturing closely restores a product to its original physical and warranty characteristics [6]. However, the introduction of remanufacturing can give rise to various challenges. At the product level, researchers have pointed out that remanufactured products can compete with new ones, leading to cannibalization [7, 8]. Additionally, the quantity of remanufactured products is limited by the quantity of new products [9], necessitating the adoption of hybrid systems. At the process level, significant investment costs may be required in the initial stages, and ongoing process innovation efforts are needed to ensure the profitability of the practice [10]. On the technical level, scholars criticize the difficulty of assessing the quality, reliability, and maintainability of remanufactured products [11]. Similarly, due to a lack of education, customers may perceive remanufactured products as having lower value and higher risk [12]. Lastly, the implementation of remanufacturing involves significant complexity and coordination among actors to effectively and efficiently deploy a closed-loop supply chain (CLSC) [7].

To facilitate the implementation of practices and processes, the literature offers various tools, including readiness models (RMs). Readiness refers to the attitude towards a specific change [13]. Readiness assessments serve as diagnostic tools to analyze and determine the level of preparedness at all levels of a system, aiming to clarify whether an organization is ready or not to embark on the development

process [14]. Assessing the level of readiness increases the likelihood of a successful initiative introduction [4]. However, there is a lack of maturity models considering the readiness of CE practices enabled by remanufacturing processes [15]. Thus, this work aims to develop a RM to implement Remanufacturing for CE (R4CE) adoption in CLSCs. The R4CE model follows a multi-methodological design approach consisting of three procedural steps [16]: content search, literature review, and model proposal. The first methodology involves conducting a systematic literature review on RMs for remanufacturing and CE practices to identify literature gaps. The second methodology applies a systematic literature network analysis to examine the adoption of remanufacturing in CLSCs, quantitatively identifying dimensions and sub-dimensions. Finally, by refining the results of both methodologies, we propose the novel R4CE model.

To provide an overview of the article structure, Sect. 2 presents the methodology employed. Section 3 includes the research results, content analysis, and the proposed model. Finally, in Sect. 4, we present the conclusions and outline future developments.

2 Methodology

In the literature, two commonly used design approaches for developing maturity models [17, 18], including RMs, are often identified. These two approaches involve dividing the process into phases such as need identification, scope definition, model design, design evaluation, and model retention. However, potential model designers often encounter challenges when it comes to selecting the dimensions and sub-dimensions, which may require extensive efforts in literature search [1] or iterative engagement with practitioners [3] to ensure reliable results. To address this issue, we propose an innovative multi-methodological approach that integrates a Systematic Literature Review (SLR) and a Systematic Literature Network Analysis (SLNA) in this work. Our approach follows a three-step methodology, comprising literature research, content analysis, and model proposal (see Fig. 1).

The first step of the literature research involves identifying the most relevant references from two research strands. The first strand focuses on the identification of RMs using an SLR approach. The objective in this stage is to classify the literature and highlight any existing gaps. The second strand, on the other hand, involves selecting references related to remanufacturing (REM) adoption in CLSCs using an SLNA approach. Through this analysis, the aim is to cluster the literature and examine domains and subdomains for the proposed readiness model, named R4CE. The search database used for both strands was Scopus.

To conduct the searches, appropriate search queries were constructed by combining keyword groups and logical operators. The logical operator 'OR' was used to combine keywords within the same group, while the operator 'AND' was used to combine different groups of keywords. The '*' operator was employed for single keywords to capture terms with a common root, and the 'W/I' operator was

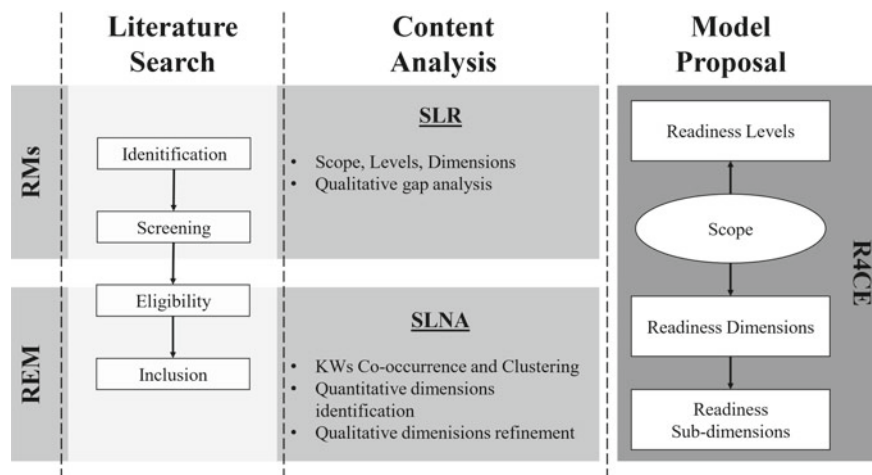


Fig. 1 Proposed three-step methodology integrating an SLR and an SLNA

used to establish a sequential order between two keywords, allowing for the presence of any single word in between. The searches were performed in the fields of title, abstract, and keywords. For the topic of RMs, the following search string was used *TITLE-ABS-KEY (((readiness W/1 model) OR (readiness W/1 framework) OR (readiness W/1 roadmap) OR (readiness W/1 grid) OR (readiness W/1 assessment) OR (readiness W/1 level) OR (readiness W/1 index)) AND (remanufactur* OR “circular economy”))* while for REM process the following *TITLE-ABS-KEY (remanufactur* AND “closed-loop supply chain”)*. The identified articles were then filtered based on the following inclusion criteria:

- Papers related to the fields of “Engineering,” “Environmental Science,” “Business, Management, and Accounting,” and “Decision Science” were considered.
- The time span was limited to the years 2010–2022.
- Only articles and reviews were included.
- The language of papers was limited to English.

In the SLR approach, the remaining articles underwent a screening process to include those relevant to the development, validation, and application of RMs in REM operations. The screening process involved reviewing the title, abstract, and keywords, followed by a full-text analysis. From this screening, a final set of 5 articles was identified as relevant for investigating the main RMs, and these articles were included in the analysis. To conduct the SLNA methodology and investigate the REM in CLSCs, the screening process was less detailed. As a result, the titles of 621 articles were reviewed, and 533 sources were selected for further analysis. The partial results obtained from each search query, after applying the inclusion criteria, are presented in Table 1.

Table 1 Results of inclusion criteria

Criteria	SLR on RMs	SLNA on REM
Keywords	56	1,120
Subject area	42	995
Time	39	824
Document type	31	697
Language	31	621
Eligibility	8	533
Included	5	533

The second step of the methodology involves comparing the results of RMs with the clusters of REM process. The RMs will undergo qualitative gap analysis, while the results of the REM process in CLSC will be processed through co-occurrence and thematic map analyses of the indexed keywords in the selected papers. This analysis serves as a strategic diagram classification method [19]. Co-occurrence analysis evaluates the association strength (AS) between two keywords based on the semantic relatedness [20]. It is calculated using Eq. (1), where $a_{jj'}$ represents the number of co-occurrences of keywords j and j' , and $\hat{a}_{jj}$ and $\hat{a}_{j'j'}$ are the expected number of co-occurrences of keywords j and j' .

$$AS_{jj'} = \frac{a_{jj'}}{\hat{a}_{jj} * \hat{a}_{j'j'}} \tag{1}$$

AS ranges from 0 to 1, with values closer to 0 indicating less co-occurrence and values closer to 1 indicating stronger co-occurrence. Using community detection, K thematic clusters can be identified. For each cluster, the Callon Centrality (CC) and Callon Density (CD) values are calculated using Eqs. (2) and (3). CC represents the degree of relevance of the cluster within the domain, while CD represents the degree of development [21].

$$CC_k = 10 \sum_{j \in k, h \in k'} AS_{jh} \tag{2}$$

$$CD_k = 100 \sum_{j, j' \in k} \frac{AS_{jj'}}{n_k} \tag{3}$$

CC and CD allow for the creation of a thematic map that categorizes keywords into four quadrants. The top right quadrant represents highly developed and research-relevant topics, labeled as *motor themes*. The upper left quadrant represents *niche themes*, which are very specific with few relationships. The lower left quadrant describes *emerging or declining themes*, indicating underdeveloped topics. Finally, the lower right quadrant includes keywords that are relevant for the search but are treated in a general manner, referred to as *basic themes*. Additionally, the co-occurrence analysis helps refine the selection of dimensions and sub-dimensions by

graphically illustrating the relevance and relationships among the keywords in the papers. The most relevant references, consistent with the results of the thematic map, are qualitatively analyzed, taking into consideration their Impact Factor (IF) value, calculated using Eq. (4). IF is determined by the total number of citations (TC) and the time elapsed since the year of publication (PT).

$$IF = \frac{TC}{PT}$$

(4)

In the third step of the methodology, a new RM named R4CE will be proposed, incorporating the findings from the second step. The R4CE model will identify the model elements, including levels, dimensions, and sub-dimensions.

3 Results

The relevant information for the design of R4CE readiness model was examined from a quantitative and qualitative point of view. The SLR used a spreadsheet, while the SLNA used the Bibliometrix package as a R-tool for science map analysis [22]. In Sect. 3.1 the detailed results of the RMs literature review are given, and in Sect. 3.2 those for REM. The combination of the results in Sect. 3.3 leads to the R4CE proposal.

3.1 SLR on RMs

The SLR identified a total of five RMs that were analyzed in detail, focusing on their architecture (levels (L) and dimensions (D)) and application content. These findings are summarized in Table 2.

In terms of architectural elements, the RMs can be categorized into two types. The first type measures the level of readiness using a percentage indicator of adoption, while the second type uses a discrete number of levels. Among the discrete models,

Table 2 Results of the 5 articles on REM and CE RMs

Ref	REM	L	D	CM	CLSC	P&R
[13]	X	0–100	6	X	–	–
[14]	–	6	5	X	–	–
[23]	–	4	8	–	X	–
[1]	–	6	8	X	X	X
[4]	–	0–150	8	X	–	X

Note reference (Ref), remanufacturing (REM), number of levels (L), number of dimensions (D), collaboration mechanisms (CM), closed-loop supply chain (CLSC), policies and regulations (P&R)

two utilize a 6-level scale [1, 14], while one adopts a 4-level scale [23]. Regarding dimensions, the majority of the RMs describe readiness through eight dimensions. The models can also be classified based on their application focus. Most of them address readiness considerations at the organizational level [1, 4, 14], while a few touch upon processes [23] and products [13]. Only one model explicitly evaluates the readiness of the remanufacturing process [13], while the others generally assess the readiness for introducing CE practices.

It is worth noting that several scholars emphasize the importance of collaboration mechanisms (CM), strategic decisions within the CLSC, and policies and regulations (P&R) in facilitating the adoption of CE practices, including REM. However, among the five identified models, only [1] considers all three elements in an integrated manner, specifically addressing the assessment of smart circular supply chain readiness and maturity at a general level.

Based on these observations, it can be concluded that the literature may not provide a dedicated RM for the adoption of remanufacturing in the context of CE practices within CLSCs.

3.2 SLNA on REM

The results of the co-occurrence analysis revealed the presence of six clusters in the REM literature based on CC and CD calculations. These values were used to classify the clusters into different quadrants on the thematic map (see Fig. 2).

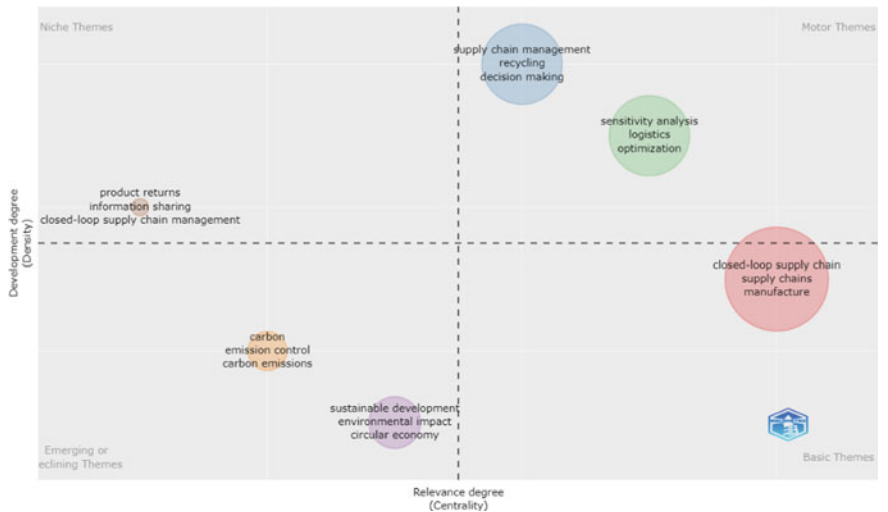


Fig. 2 Thematic map of remanufacturing in closed-loop supply chains

The cluster with the highest significance was the “Closed-loop supply chain” cluster, which had 2,161 occurrences across 79 KWs. This cluster fell within the basic themes’ quadrant as the only cluster in that category. Within this cluster, the KW related to remanufacturing was present. The “Supply chain management” cluster (733 occurrences on 59 KWs) and the “Sensitivity analysis” cluster (727 occurrences on 77 KWs) were categorized as motor themes. The “Product returns” cluster (37 occurrences on 7 KWs) was the only niche theme identified in the analysis, specifically related to the topic under investigation. Lastly, the clusters of “Sustainable development” (190 occurrences on 17 KWs) and “Carbon” (104 occurrences on 11 KWs) were positioned in the emerging or declining theme quadrant. These findings provide insights into the distribution and relevance of KWs, allowing for the refinement and selection of dimensions and sub-dimensions for the proposed R4CE model.

3.3 R4CE Proposal

The SLR analysis indicated that only one RM directly addressed remanufacturing, but it focused on product readiness rather than CLSC [13]. Additionally, the thematic map derived from the SLNA analysis identified six clusters, some of which shared common concepts and general outputs of introducing practices. To address these findings, a qualitative criterion was used to complement the quantitative SLNA results, leading to the identification of three recurring dimensions. Articles with an IF level greater than or equal to 25 were analyzed to ensure the relevance of the selected dimensions.

The proposed R4CE readiness model is presented in Fig. 3. The model assesses the readiness for introducing remanufacturing within CLSC based on three dimensions: **collaboration mechanisms** (D1), **CLSC decisions** (D2), and **policies and regulations** (D3). Each dimension further consists of three sub-dimensions.

Indeed, collaboration and competition strategies have been identified as facilitating the introduction and retention of remanufacturing by several scholars. Given the complexity of the CLSC system, it becomes crucial, especially in the initial stages, to promote the sharing of resources and information among the actors involved. Examples of such collaborations include technology licensing, where CLSC actors share their technological advancements [3, 24, 25]. Moreover, active cooperation among the various CLSC actors, such as suppliers, manufacturers, and remanufacturers, is essential during the early design phases. This can be achieved through establishing R&D collaborations [3, 26] and adopting a design-for-remanufacturing approach [6]. While sharing benefits within organizations at different levels of the CLSC can be challenging, it becomes even more complex when it comes to consumers. Customer education and awareness play a crucial role in the successful introduction of remanufacturing. Customers who are aware of their consumption behavior [27], consider factors such as cost and quality [12, 28], and have a positive value perception and preference for sustainable/green purchasing choices [8, 27–29]

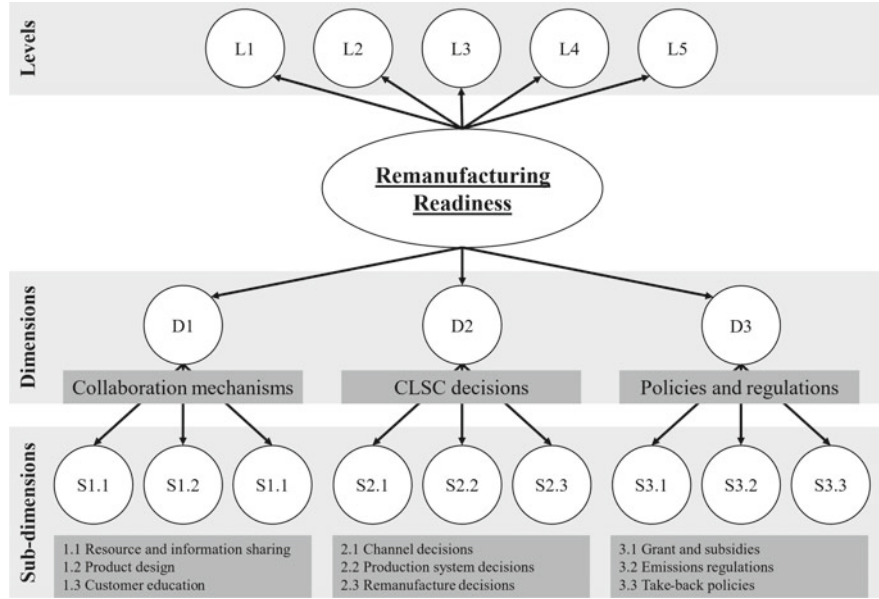


Fig. 3 R4CE proposal assesses the remanufacturing readiness for CE adoption in CLSCs through 5 levels (L), 3 dimensions (D), and 9 sub-dimensions (S)

are more likely to embrace remanufactured products. Therefore, within the collaboration mechanisms dimension, the three sub-dimensions are identified as: **resource and information sharing** (S1.1), **product design** (S1.2), and **customer education** (S1.3).

From a strategic network decision-making perspective, it is crucial to analyze the advantages and complexities associated with different activities that can be outsourced to gain a competitive advantage. In the context of remanufacturing, the decision maker needs to assess whether the production system should be used solely for the remanufacturing process or in a hybrid manner for both manufacturing and remanufacturing processes [7, 30, 31]. This decision is important because the quantity of remanufactured products is directly linked to the quantity of new products, which introduces complexities in configuring sales and collection channels. Furthermore, to effectively manage the forward and reverse flows within the CLSC and satisfy all actors involved, it becomes necessary to identify the most suitable actor among manufacturers, retailers, or third-party providers to handle these flows. This decision involves determining the optimal allocation of responsibilities for managing the forward flow of products (from manufacturing to consumers) [7, 31, 32] and the reverse flow (from consumers to remanufacturing processes) [6, 24, 29, 33]. Finally, deciding who should be responsible for carrying out the remanufacturing activity is not always straightforward [6, 8, 27]. The literature highlights the complexity of this

decision, which can involve considerations such as organizational capabilities, expertise, and resources. Identifying the most appropriate actor to carry out the remanufacturing process is a critical aspect of CLSC decision-making. Therefore, within the CLSC decisions dimension, the three sub-dimensions are identified as follows: **channel decisions** (S2.1), **production system decisions** (S2.2), and **remanufacture decisions** (S2.3).

Another crucial factor that facilitates the introduction of remanufacturing is the presence or absence of policies and regulations. Scholars have highlighted the benefits of certain policies and regulations in promoting and supporting remanufacturing initiatives. For instance, subsidies provided to consumers who purchase remanufactured products have been identified as a favorable policy [7, 34]. Additionally, investments in carbon reduction technologies have been recognized as a facilitator for remanufacturing [27]. Environmental and return regulations are also effective instruments in promoting remanufacturing. Emission regulations, such as carbon tax, cap-and-trade systems [27, 35], and mandatory carbon emission capacity regulations [27], have been explored by researchers in relation to their impact on remanufacturing. Furthermore, various authors have assessed the effects of take-back policies, including deposit-refund systems [36], reward-penalty mechanisms [29], as well as buy-back and trade-in programs [3]. Considering these policy and regulatory practices, R4CE incorporates the following three sub-dimensions within the policies and regulations dimension: **grants and subsidies** (S3.1), **emissions regulations** (S3.2), and **take-back policies** (S3.3).

The readiness of introducing the remanufacturing process within CLSC can be classified into five levels: L1 (completely unready), L2 (partially unready), L3 (neither unready nor ready), L4 (partially ready), and L5 (fully ready). These levels correspond to the decision maker's awareness of the context and their ability to exploit collaboration mechanisms, CLSC decisions, and policies and regulations.

4 Conclusions and Future Developments

The scarcity of resources and the increasing environmental concerns necessitate a reevaluation of processes, techniques, and organizational cultures. In this context, the adoption of CE concepts, including remanufacturing, offers a pathway to achieve competitive goals while ensuring environmental and social sustainability. However, implementing these practices is not without challenges and often requires collaboration among different actors in the supply chain, customer education, and supportive policies and regulations. To address this need, the article proposes a RM that assesses the readiness for introducing remanufacturing in the design of CLSCs. The work presented in this study offers both academic contributions and practical implications. In terms of academic contributions, the RM is developed through an innovative design approach that incorporates SLR and SLNA methodologies. By conducting a comprehensive analysis of the existing literature on remanufacturing and CE, a gap analysis is performed to identify quantitative and qualitative dimensions for the

introduction of remanufacturing in CLSCs. The integration of these dimensions leads to the formulation of a five-level R4CE model, represented by the three key dimensions of CM, CLSC, and P&R. In terms of practical implications, researchers and practitioners can enhance their understanding and application of readiness assessment for introducing remanufacturing in CLSCs, contributing to the advancement of sustainable and circular business practices.

While the proposed RM holds academic and practical relevance, it is important to acknowledge its limitations, which can be addressed in future research. Firstly, the identification of dimensions in the RM relies on a quantitative approach that can be further improved by employing a list of common words to consolidate similar terms within a single cluster. Secondly, the model lacks empirical validation and is based on a theoretical foundation. Future work can involve validating R4CE through structured questionnaires administered to both academic and industry experts, followed by statistical analysis of the obtained results. Finally, the model could be enhanced by integrating the concepts of maturity and capability assessment to evaluate the utilization and continuous improvement of organizations that have already implemented remanufacturing process.

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Tools and Methods for Designing Mechanical Components for Multiple Remanufacturing Cycles in Agricultural Machinery



Stefano Beneduce, Amelia Felaco, Mario Munno, and Francesco Caputo

Abstract This work addresses the relevant issue of objectively evaluating the useful life of mechanical components through life cycle and cost analysis, when destined to remanufacturing in agricultural machinery field. The goal is to identify the most efficient strategic choices for predicting and managing the end of life of a component/product to maximize profit and minimize consumption of economic and natural resources. The approach of Design for Remanufacturing and Design for Extension of Life is presented as effective solutions to extend the useful life of structural mechanical components, making them suitable for multiple remanufacturing process, and emphasizing the importance of considering long-term implications on the product and entire system life cycle. Life cycle analysis (LCA) and costing (LCC) are described as the proper tools to evaluate alternatives and identify which design scheme can ensure maximum profit and minimum consumption of material and energy. Specifically, the article proposes a methodology to compare between producing more components with the current design that will undergo fewer rework cycles or producing fewer components with the updated design that will undergo more regeneration cycles. The main questions that the article seeks to answer are: to what extent is it profitable, from an economic and natural resource perspective, to extend the useful life of a structural mechanical component in prevision of remanufacturing processes? What is the design scheme that can ensure maximum profit and minimum consumption of material and energy? Objective evaluation of process alternatives, considering design for remanufacturing and life extension, can provide a multi-objective optimal solution that maximizes product value and minimizes environmental impact.

Keywords Design for remanufacturing · Design for extension of life · Life cycle assessment-costing · Multi-objective optimization · Resource consumption

S. Beneduce (✉) · A. Felaco · M. Munno · F. Caputo
Department of Engineering, University of Campania “Luigi Vanvitelli”, via Roma 29, 81031
Aversa, CE, Italy
e-mail: stefano.beneduce@unicampania.it

1 Introduction

Environmental issues, such as climate change, waste generation and resource scarcity, are significant concerns of our time. Governments and industries worldwide are focusing on reducing pollutants to protect natural resources for current and future generations. The European Union, for instance, approved the European Climate Law with the goal of reducing greenhouse gas emissions by at least 55% by 2030 and achieving climate neutrality by 2050 as part of the European Green Deal [1]. A circular approach is necessary to foster sustainable and resilient businesses and remanufacturing processes play a crucial role in enabling the Circular Economy effective implementation [2].

Compared to traditional manufacturing, remanufacturing can significantly reduce the use of raw materials, water, energy consumption, pollutant emissions and land-fill requirements for the same amount of commercialized product. Not only. The European remanufacturing industry already employs over 500,000 people and is projected to triple by 2030, reaching an estimated value of €100 billion [3]. To achieve this forecast, it is essential to enhance remanufacturing processes, overcome operational, economic, and social barriers, and make remanufacturing more profitable and appealing to all sectors of production and consumers. Many are the challenges that must be solved to make remanufacturing effective and profitable, both environmentally and economically, but above all what it is certain is that products must be conceived and designed with this purpose in mind; all factors related to remanufacturing should be considered during the design phase of industrial products [4]. Designing with a focus on environmental sustainability and circularity involves to attribute properties to the products that make them such as to establish closed loops for production, consumption, and recovery and, consequently, such as to minimize material and energy flows [5].

In this scenario the heavy industrial, agricultural, and earthmoving machinery sector is particularly representative. In recent years, in fact, remanufacturing techniques have gained popularity in this field. These techniques involve the recovery and regeneration of used components, which are then reintroduced into the market through spare parts channels and warranty services. This mechanism provides a cost-effective alternative for both OEMs and end-users, reduces environmental impact, and ensures component availability during periods of limited primary source procurement. To better understand the impact and potential of Heavy-Duty and Off-Road remanufacturing market it is sufficient to consider that the European tractor market in 2021 reached almost the peak of 159,000 registrations, a volume that is almost 19% higher than that of 2020 [6]. In the European Union approximately 20 million HDOR vehicles are in use (light vehicles are 270 million) of which 1 million are disposed of each year [7]. These vehicles and machines are characterized by an estimated operational life of 12 years, useful life of 10,000–12,000 h, technical obsolescence is estimated to occur at around 10 years [8]. The reality is that useful life of a tractor, especially for small agricultural companies in Western Europe, ranges from 28 to 34 years [9]. It appears evident that with such a long operational life of the machine,

end-users are inclined towards repairing their own vehicles and will necessarily have to turn to spare parts for the replacement of components.

Remanufacturing in the agricultural sector is more and more understood and accepted and fits itself very well for structures that are relatively simple, robust and metal-oriented, characterized by high rate of recoverability, recyclability, and remanufacturability [10].

There is a high level of activity in remanufacturing applied to HDOR machines, the vast majority of which occurs on engines, gearboxes, supercharging groups and hydraulic pumps, all parts characterized by high intrinsic value, both economic and energy. Structural optimization of these components should focus on ensuring their integrity over multiple life cycles and minimizing waste during the remanufacturing process. To ensure functionality equal to new components and reduce waste during assembly, it is essential to optimize the product design process and adapt it to new requirements for service life and technological advancements. However, the shift towards a more effective recovery and mechanical regeneration of industrial products necessitates innovation in the product development process. Energy, resource, and economic efficiency are the primary parameters that should characterize such products, but often they are very poorly included in the dimensioning process of mechanical parts [11]. Innovations are needed to make components and systems more durable, more sustainable and suitable for integration into the recovery and remanufacturing process, while maintaining high-quality and performance standards.

Based on this concepts, the proposal for this work is to generate a framework that can guide product designers in including life cycle, specifically remanufacturing, requirements into the final size of a product. This concept arises primarily from the analysis of a real remanufacturing process applied by a leading company in the heavy machinery and agricultural equipment sector. Such company, that operates in the commercial vehicles and agricultural machinery industry, focuses on refurbishing and regenerating used mechanical and electronic components to extend their useful life and reduce environmental impact, reintroducing them to the market through spare parts channels and maintenance service. The activities include the collection of used components from a wide range of industrial and agricultural equipment, including tractors, harvesters, construction vehicles, and other machinery. These remanufactured products provide a reliable and cost-effective alternative to purchasing new parts, allowing customers to save money while contributing to sustainability.

The paper will be structured starting in Sect. 2 with a review of the state of the art of Design for Remanufacturing; in Sect. 3 the study case remanufacturing process will be described; in Sect. 4 the framework will be developed and described; in Sect. 5 conclusion and further development will be summarized.

2 Design for Remanufacturing: Practice and Standards

Remanufacturing is an industrial process that aims to restore the usefulness of consumption goods and products. Remanufactured products undergo a restoration process that brings them back to their original specifications, ensuring their structural integrity, safety, and environmental impact. The British standard 8887-220:2010 defines remanufacturing as the series of steps required to transform an old product into one that can be considered as new, with equal or better performance and warranty compared to a new product. The exact sequence and type of operations that an object undergoes during a remanufacturing process depend a lot on the object itself and the requirements to be met, but it is possible to generalize a list of generally valid phases. A generic remanufacturing process always includes: Recovery, Disassembly, Cleaning, Inspection, Machining, Assembly and Testing [3].

The implementation of such a process necessitates products to possess specific characteristics that enable them to undergo the process. The effectiveness and efficiency of remanufacturing in fact heavily rely on decisions made during the product design phase [12]. It is evident that products must be designed proactively to accommodate remanufacturing. Designing with the objective of establishing closed production, consumption, and recovery cycles to minimize material and energy flows (e.g., raw materials, energy, waste) involves making choices that not only meet structural and functional requirements but also facilitate easy access to the recovery phase and equip products with the necessary technical characteristics for all the steps of the process. However, there are several barriers to the implementation of remanufacturing processes. Technical barriers pose significant challenges for companies aiming to enter the remanufacturing business. Remanufacturing processes involve uncertainties due to the varying conditions of returned products. Two identical products can have different quality conditions based on service use. This generates issues related to uncertainty in the components that can be recovered from each product, as well as uncertainties in the required tasks and processing times during the remanufacturing process.

Design for Remanufacturing encompasses a set of tools and methods aimed at conceiving and designing products as much as possible suitable for the remanufacturing process, enabling multiple life cycles. It is important to note that some features influencing remanufacturing may have conflicting impacts on other activities (e.g., weight, functionality, production cost), which often makes Design for Remanufacturing becoming a multi-criteria decision-making process that must include life cycle and cost considerations [13].

Given the numerous requirements and technical needs associated with this process, remanufacturing-oriented design encompasses several objectives, with a primary focus on enabling disassembly (Design for Disassembly) and ensuring structural integrity for an extended period (Design for Durability). To incorporate these objectives into the design phase, it is crucial to establish closed-loop information transfer systems between the process and design. Communication of this nature often represents a major barrier to remanufacturing. Gathering information during

the disassembly and inspection phases becomes crucial for providing feedback to the design team, facilitating remanufacturing-oriented design improvements for new products. Barriers and difficulties encountered during disassembly, as well as the frequency and types of damage or failures, provide critical information for rethinking and updating the part's design. This enables design improvement based on statistical analysis and life cycle thinking, ultimately enhancing remanufacturing performance of new products [14].

Currently, methodologies for designing structures for remanufacturing purposes are not well-established, and integration of LCA and LCC parametrization is still limited in terms of confidence and economic accessibility [15]. Despite these challenges, remanufacturing processes can still be achieved without extensive optimization and quality improvements. However, the new requirements for recovery and processing necessitate a change in the overall design approach, considering specific structural needs, processing technologies, and component utilization. Calculations and simulations will play a crucial role in predicting behavior during subsequent life cycles and considering possible structural updates.

Given this landscape and the lack of this kind of study cases found in literature, the paper aims to propose new framework and corresponding production processes that prioritize extended service life of products destined to remanufacturing, based on feedback coming from the process itself.

3 The Study Case: Remanufacturing Process

The aim of this paper is to propose a methodological approach, intended as a tool that can guide in the design iteration of machine organs in anticipation of remanufacturing cycles. The elaboration of this series of operations is based on the feedback that was obtained by investigating a real remanufacturing process performed on agricultural machinery propulsion and transmission systems.

The remanufacturing process is analyzed and described to show the specific requirements of each phase, the reasons leading to the exclusion of components, and the approach followed to ensure functionality and warranty of the reman parts. This specific process is based on main concepts listed below:

- a. The history of the cores is not taken into account in remanufacturing;
- b. The process indeed loses the traceability of the original core of the individual components. All of them are treated in the same way regardless of their origin;
- c. A component can undergo the remanufacturing process as long as it meets the design specifications of the equivalent new;
- d. No damaged component is accepted in the final assembly;

It involves a series of operations that unfold according to the sequence shown in the following block diagram (Fig. 1) and explained below.

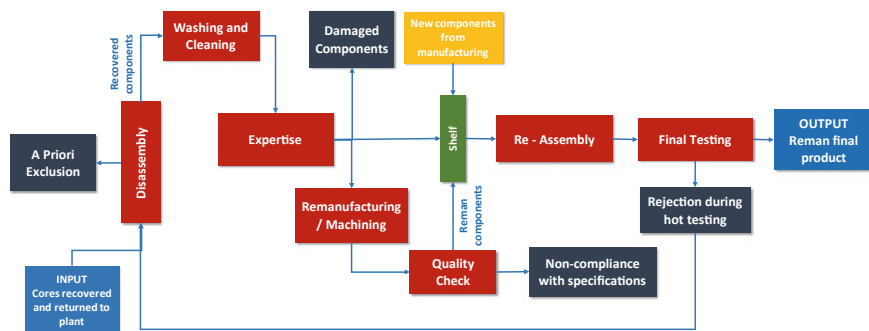


Fig. 1 Study case remanufacturing process

3.1 Core Recovery

Core recovery is the first step of the process, it includes all the operations and strategies implemented through sales and service channels to recover cores that have reached the end of their useful life. It will not be investigated as it involves marketing and logistics aspects that deviate from the focus of this work, which is mainly the product and the design.

3.2 Disassembly

Once the products have been recovered at the end of their life, they reach the remanufacturing facility. This is an essential step that involves breaking down a complex product into all its parts, making it possible for all subsequent operations. The actual process begins with the complete disassembly, mostly done manually. Disassembly prepares all the assembly components for the subsequent washing and cleaning phase. It is important to note that from this point onward, the components lose traceability, meaning the indication of the core's origin is not maintained. From the subsequent phases onwards, the components will be processed in the same way and randomly reinserted into the final remanufactured assembly.

3.3 Washing and Cleaning

This step is necessary to remove any material collected during use. Different techniques of cleaning are performed to remove all impurities, dirt residues, and working fluids. If necessary, paint and rust removal operations in this phase are also carried out.

3.4 Expertise

After cleaning, the components that continue the process undergo inspection. Each component is analyzed by experts to decide remanufacturability. The task is primarily carried out manually, with visual inspections of an operator that is supported by manuals to compare the component's condition against references. For more critical parts this phase also involves non-destructive testing to identify any defects. Techniques used can be liquid penetrant testing (to detect surface defects) and X-ray testing (to detect deeper cracks). This phase is critical as it determines the health status of the components and whether they can proceed or not in the process.

3.5 Remanufacturing/Machining

This phase involves components that require the restoration of certain properties and specifications. Major operations include general reparations, grinding and surface finishing to restore surface roughness conditions, restore geometries, and eliminate surface crack initiation. These operations primarily involve material removal which involves some alteration of the original specifications that will have to be balanced by the other components where possible.

3.6 Quality Check

To ensure that the remanufactured components meet the same functional requirements as new components, all reman components intended for use in the final regenerated product must satisfy the same design requirements as their new counterparts. For this reason, all the parts undergo measurements and checks that determine their inclusion or exclusion. Parts that pass this phase are shelved and ready to be used in the assembly of the finished product.

3.7 Re-assembly

This phase replicates the assembly process of a new product. Regenerated components are randomly taken from the shelf, integrated with new parts, and undergo the entire assembly line in the same way as a new product to ensure the same requirements are met.

3.8 Final Testing

The finished assembled product undergoes hot testing, to ensure that remanufactured parts properly work in the finished assembly product.

The process maintains the characteristic features of a generic remanufacturing process. From a product perspective, it appears evident that to improve the process and make it more efficient it is necessary to investigate the causes of waste produced during the described process, specifically the reasons that cause a component to be rejected from remanufacturing (because damaged) or after quality inspection (because no longer respond to original specification). As observed from the block diagram (Fig. 1), four main sources of waste have been identified during the specific process, each with its specific reasons. The following cases of waste occur for all cores entering the process during various phases:

1. **A priori exclusion:** this is the waste that occurs immediately after the disassembly phase. In addition to all elements characterized by high wear and tear, like seals and bearings, this category includes all structural components that are heavily stressed during operation (such as pistons, gears, friction plates, etc.) and for which sufficient confidence cannot be established for reuse.
2. **Damaged components:** The reman process does not accept the reintegration of damaged components into the assembly. This category includes both visibly damaged components and those that, following the expertise, show signs of damage and cracks. No tolerance is applied, the presence of damage results in exclusion.
3. **Non-compliance with specifications:** Machining operations, which often involve restoring geometries and surface finishes by material removal, can alter the dimensional specifications of the treated object. If these specifications deviate from the design values to a point where the component can no longer meet the requirement, it should be excluded.
4. **Rejection during hot testing:** This case is rare and involves the failure of the final assembled product. It occurs when anomalies were not detected during previous phases.

As said the main task to optimize the efficiency of the process, from a product point of view, is to reduce the waste and ensuring that the highest possible rate of components will be reintegrated in the final remanufactured assembly. There are four main sources of waste during the process. Each of them should be monitored and should constitute feedback for the design. The analysis of field feedback related to components damage analysis and exclusion causes are aimed at extending the useful life of parts and consequently reducing the number of parts discarded during the remanufacturing and assembly process, with the aim to expand the remanufacturability of parts and ensure multiple life cycles.

4 The Proposed Framework

Based on the information and description provided, from a product design perspective, two fundamental questions need to be considered in anticipation of such a process:

1. Based on the feedback received from the process, what are the critical points in the design specifications that need intervention to minimize deviations and extend the lifespan of components?
2. To what extent is it economically and environmentally advantageous to extend the lifespan of an object and enable multiple remanufacturing cycles?

The answers to these questions are not straightforward and require a process of which the final output will be the dimensioning of parts. The process involves considering design modifications, conducting analyses of environmental and economic impacts, and ultimately evaluating the benefits and drawbacks of extending the lifespan of the object through remanufacturing.

A design process oriented to multiple remanufacturing can be approached according to the framework showed in Fig. 2 and described in the following sections.

4.1 Component Design Specification Analysis

The first step is to identify a product/component that results in high rate of scrap, because of high rate of failure, or a component that will undergo machining operations during the remanufacturing process. Once the statistical analysis on parts has been performed, it is important to obtain design specifications including drawings, dimensions, materials, CAD files, and Finite Element Analysis (FEM) results.

Alongside it is necessary to understand both new production and the remanufacturing process, considering changes in component characteristics during and after the remanufacturing, and assess the health status of the component as it goes into and comes out of the regeneration process.

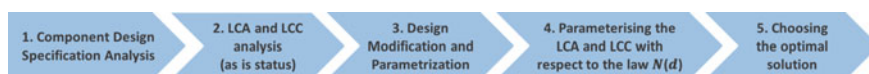


Fig. 2 Proposed framework

4.2 *Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) Analysis*

Alongside with technical specifications, related to design and process, it is fundamental to gather data on the environmental and economic impacts of both the new production process and the remanufacturing cycle of the specific component. This step is necessary to model these processes (as-is status) with their respective environmental and economic loads and so to perform Life Cycle Assessment (LCA) and Life Cycle Cost (LCC) analyses using dedicated software. This comprehensive analysis aims to encompass the entire life cycle, encompassing initial manufacturing phases along with successive remanufacturing cycles, all within the context of the existing design.

4.3 *Design Modification and Parametrization*

Knowledge of the technical specifications allows at this point to intervene in the design with the aim to extend product's lifespan, for instance, through changes in relevant factors. Changing design specifications and perform structural analysis allows to identify a relationship between the component's design "d", which in the most general case can be considered as a vector of multiple variables, and the number of remanufacturing cycles N it can undergo through a functional link that can be expressed like:

$$N = N(d)$$

4.4 *Parameterizing LCA and LCC with Respect to the law $N(d)$*

Change in the design will influence the number of possible remanufacturing cycle. Schematizing the problem as such effectively constitutes a parameterization of the number of remanufacturing cycles, and with it the lifecycle, with respect to the design specifications of a particular component. Establishing this functional link between the technical features of an object and the number of remanufacturing cycles it can undergo falls within the responsibility of the designer. By incorporating the aspects of the remanufacturing process, the designer can inherently link them to the impacts/costs arising from the whole lifecycle.

For each design alternative d it is possible to create a table like the one reported below (Table 1).

Table 1 Schematized functional link for each design alternatives d

Lifecycle step	# i	$Cost_i(d)$	$Impact_i(d)$
Initial manufacturing	0	$C_0(d)$	$I_0(d)$
Remanufacturing 1	1	$C_1(d)$	$I_1(d)$
Remanufacturing 2	2	$C_2(d)$	$I_2(d)$
.....	...	...	...
Remanufacturing N	$N(d)$	$C_N(d)$	$I_N(d)$

4.5 Choosing the Optimal Solution

Having constructed such a table for different design alternative, it is possible to evaluate the total cost and impact for each according to the general relationships below:

$$C_{Tot} = f[d, N(d)] = \sum_{i=0}^{N(d)} C_i$$

$$I_{Tot} = g[d, N(d)] = \sum_{i=0}^{N(d)} I_i$$

Usually, as confirmed by findings and calculation, values of this functions are sum of non-linear functions that makes it highly non-linear. To make the operation simple, it is possible to perform a simple DOE in which calculation of total cost or impact can be implemented for a certain number of design alternatives, and reporting results on a table (see Table 2) or plotting a curve on a diagram (see Fig. 2).

The diagram (see Fig. 3) is intended to give qualitative representation of the value of the whole life-cycle cost/impact linked to the number of remanufacturing cycles, which in turn is directly linked to the product design specifications. The design scheme that ensures minimization of costs and impacts is so defined as follow:

$$\bar{d}: C_{Tot} = g[\bar{d}, N(\bar{d})] = C_{\min}$$

$$\bar{d}: I_{Tot} = g[\bar{d}, N(\bar{d})] = I_{\min}$$

It is important to remind that in the most general meaning, d is a solution vector that includes material, geometry and size quantities.

Table 2 Table of total cost/impact for n design alternatives

Total cost/Impact	d_1	d_2	d_3	...	d_n
$C_{Tot} = f[d, N(d)]$					
$I_{Tot} = g[d, N(d)]$					

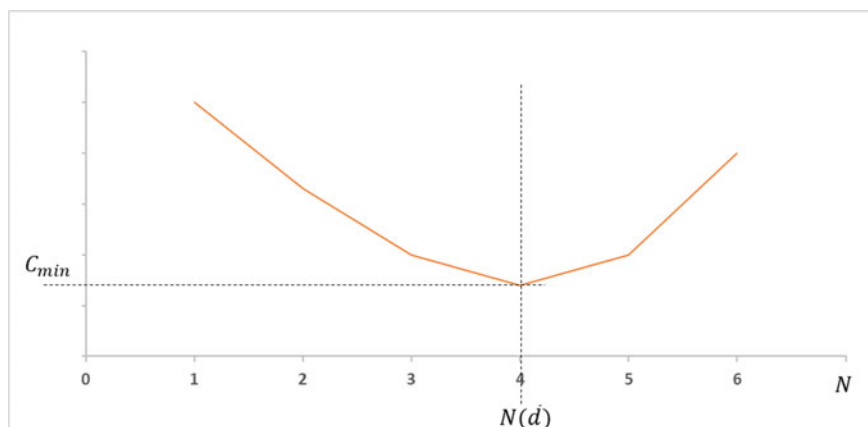


Fig. 3 Qualitative representation of minimum cost against number of remanufacturing cycles

5 Conclusion and Further Development

In the context of a real-world remanufacturing process applied to agricultural machinery field, the study outlines a meticulous step-by-step approach. The analysis unveils critical points in the process, leading to waste generation and exclusion of components. This insight is utilized to propose a framework that addresses two key questions: how to modify design specifications to minimize deviations and extend component lifespan, and to what extent extending product lifespan for remanufacturing is economically and environmentally advantageous. The holistic proposed framework interconnects product design, remanufacturing processes, life cycle assessment, and life cycle costing. By parameterizing the relationship between design specifications and remanufacturing cycles, and considering economic and environmental impacts, an optimal design scheme can be deduced. This comprehensive approach aims to not only enhance remanufacturing processes but also contribute to the broader goals of sustainable production and resource conservation, aligning with the principles of the Circular Economy and addressing the pressing environmental challenges of our time.

In conclusion the main criticism observed of this approach is the lack of detailed and precise LCA and LCC information and data for each of the material/process combination, as well as a consolidated feedback communication system between the process and the design. The method just described must be seen as a request so that new contributions and details can be added to increase its validity and capacity to reflect reality. The further step is to implement its resolution by a computational tool and to be able to specialize it for a complex study case.

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The Importance of Design for Remanufacture in Achieving Net Zero



Kingsley Oturu  and Chukwumaobi Kingsley Oluah 

Abstract With the drive to fight climate change, governments world-wide have signed up to achieving net zero. Remanufacturing is a strategy within the circular economy that can be harnessed to achieve net zero. Remanufacturing is the process whereby a product is reworked at the end of life and transformed into a product with same or higher warranty and quality specification of a brand-new product. In this paper, using a qualitative literature review methodology, it is argued that ‘design for remanufacture’ is very important in achieving net zero and has to be taken into consideration by original manufacturers along with circular business models and reverse logistics strategies to conserve energy, enable zero waste and reduce Green House Gas emissions. It is suggested that through ‘design for remanufacture’ products can be sustainably designed ‘ab initio’ in such a way that it easy for disassembly and remanufacture of products reducing pressure on landfills, energy utilisation and environmental pollution.

Keywords Design for remanufacture · Circular economy · Net zero

1 Introduction

Sustainable manufacturing meets the needs of current generations without jeopardizing that of future generations. There are a number of sustainable manufacturing strategies that make up the circular economy. These include strategies such as reuse,

K. Oturu (✉) · C. K. Oluah

Design Manufacturing and Engineering Management (DMEM), Faculty of Engineering,
University of Strathclyde, Glasgow, UK

e-mail: Kingsley.oturu@asdoonline.org.uk; Kingsley.oturu@nhs.scot

C. K. Oluah

School of Engineering & Physical Sciences, Institute of Mechanical, Process & Energy
Engineering, Heriot-Watt University, Riccarton, UK

repurposing, recycling, and remanufacturing [1]. The aim of this paper is to demonstrate the importance of ‘design for remanufacture’ in sustainable manufacturing and achieving net zero. A qualitative literature review methodology was utilized in this research with key words ‘Design for Remanufacture,’ ‘Circular Economy’ and ‘Net Zero.’ Boolean ‘and’ and ‘or’ reasoning were utilized in searches. Papers reviewed were restricted to those in English and mainly within the last two decades. The reference sections of selected papers were also reviewed for relevant papers for further review. This current paper contributes to making the link between remanufacturing and achieving net zero as well as the different conceptual terms that make up the sustainability debate. It also addresses the gap in demonstrating the importance of design in the manufacturing of products that takes cognizance of the end-of-life strategy for dealing with the product sustainably when it is decommissioned. It contributes to making clearer the different circular strategies the underpin sustainable manufacturing. With reuse, the product is reutilized with minimal cosmetic changes for its original purpose without any significant repair of the product. With repurpose, the product is reutilized for a different purpose without significant repair. With recycling the product is collected and materials processed that would otherwise have been disposed of into new products (which may be different from the original product). With recycling, the product may be melted to ‘pre-processed material’ involving more energy use and greenhouse gas emissions. In the case of remanufacture, the product is reworked to the quality specifications of the original manufacturer with warranty to match. In the case of an upgrade, there could be an increase in features and warranty [1, 2] (Table 1). For the purpose of this paper, the focus is on remanufacturing as it is more energy efficient than some of the other circular strategies such as recycling [3].

Remanufacturing is an important strategy that could help to achieve net zero. Net Zero “refers to the balance between the amount of greenhouse gas (GHG) that’s produced and the amount that’s removed from the atmosphere. It can be achieved through a combination of emission reduction and emission removal” [4]. Net zero is often understood to mean net-zero CO₂-equivalent emissions aggregated using the 100-year ‘global warming potential’ metric [5]. A couple of technologies have been developed such as air source heat pumps, ground source heat pumps and solar panels. In order for net zero to be achieved, these products have to be designed in such a way

Table 1 Circular strategies, performance specifications and warranty [1]

Circular strategy	Performance and quality specification	Warranty
Remanufacturing	Matches or exceeds original newly manufactured product	Matches or exceeds warranty of original newly manufactured product
Reconditioning/refurbishing	Does not match the performance or quality specifications of a newly manufactured product	Does not match nor exceed warranty of original newly manufactured product

that they are easy to remanufacture at their end of life. Using medical devices as a case study, it has been argued that circular product design is important for recovery of products at their end of life [6]. Design for remanufacture of products means that the products avoid going to the landfill at their end of life but can be reworked and reused as new [7, 8]. Design for remanufacture increases the life span of the product so that it is used for longer before it is discarded [9]. There is need for taking design for remanufacturing into consideration, taking cognizance of the product life cycle [10].

Remanufacturing comprises of about 6 steps (Fig. 1). These include inspection, cleaning, disassembly, reworking, reassembly, and testing [11, 12]. These processes are not necessarily linear. During inspection, the product cores are inspected visually for defects. At this point, decisions can be made as to whether the product can be remanufactured or too damaged and should be discarded. There are other sophisticated forms of inspection such as the use of ultrasound examination of products. The products are then cleaned manually or automatically. For medical equipment, the products may be sterilized to ensure that they are free from microorganisms. Disassembly is one of the most important processes in remanufacture as the product is dissected apart and checked for internal defects. Products that are not designed for easy disassembly may be destroyed in attempts to disassemble them and be difficult to remanufacture. Disassembly may be full (where the whole product is dissected apart) or incomplete (in complex products where only parts of the product is dissected apart). During reworking, the products are reworked to working condition and could involve a wide range of innovative technology (such as additive manufacturing/3D printing), localized repair, cosmetic retouch or replacement of product parts [1, 13]. With reassembly, the product is rebuilt back into a new product. It is then tested before being sent to the customer [12].

This paper is organized in 7 sections. In the first section, the concept of ‘design for remanufacture’ in achieving net zero is introduced. In the second section, an overview of design for remanufacture in achieving net zero is undertaken. In the third section,

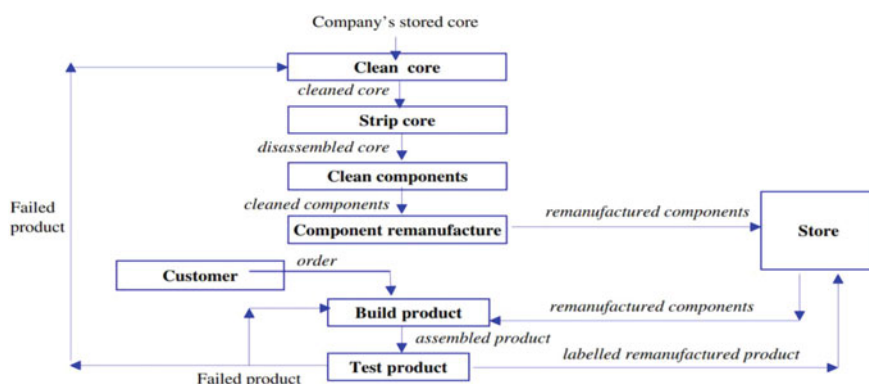


Fig. 1 The remanufacturing process [2]

deeper analysis of the role of remanufacture in achieving net zero is undertaken. In the fourth section, challenges to implementing design for remanufacture are explored. In the fifth section, tools for implementing design for remanufacture are investigated. In the sixth section, future opportunities for research are looked at, while in the seventh section, conclusions are made.

2 Overview of Design for Remanufacturing to Achieve Net Zero

The design of products involves the consideration of function or working the product through plans and drawings before the product is made. It involves innovation, with a focus on what the customer or user wants. Designs transform immaterial ideas to tangible products. It is important for designers to consider the entire life cycle of the product and how it will be disposed of or recovered at its end of life for sustainability. If a product is designed for easy remanufacture, it will be designed in such a way that it is easy for it to be inspected, disassembled, reassembled, and tested before being resented to the market [13]. It is important to note that design for a particular circular strategy may conflict with another. For example, a product may be designed for easy assembly but not for disassembly and be useful for recycling. However, the product will not be suitable for remanufacturing as disassembly is a key process in remanufacture. Market research is needed in the design of products for remanufacture. For example, products with rapid technological advancements (such as iPhones) may not be suitable for remanufacture as most customers will want to go for the latest model. Also, some phones are designed in such a way that they are difficult to disassemble without destroying the phone, making them unsuitable for remanufacture. There is need for remanufacture guidelines to support remanufacturing and guide the process [12, 13].

There are certain features in the design process that makes products easier to remanufacture. Simple products are easier to remanufacture than products with complex moving parts. Design features that aid remanufacturing include having a clean core, a smooth surface design being corrosive resistant, having non-adhesive surfaces and having easily disassembled parts. On the other hand, design features that impede remanufacturing include having complex parts, rough surfaces, strongly welded parts that are difficult to disassembly and having adhesive surfaces [1].

3 The Role of Design for Remanufacture in Achieving Net Zero

3.1 A Strategy for Waste Reduction and Extending Product Life

When products are designed with remanufacturing in mind, they ensure that the product can be recovered and remanufactured at the end of life of the product. This extends the life of the product and diverts the product from going as waste to the land fill. Remanufacturing is more energy efficient than recycling as it has a shorter recovery loop and less energy is needed [11].

3.2 Design for Remanufacture Impact on Carbon Emissions and Energy Consumption

Energy intensive processes such as melting metals to pre-processed materials are avoided in remanufacturing with less carbon emissions. It leads to lower carbon and greenhouse emissions. It reduces environmental pollutions and provides an opportunity for green jobs and research. Energy intensive processes such as melting metals to pre-processed materials are avoided in remanufacturing with less carbon emissions. It leads to lower carbon and greenhouse emissions. It reduces environmental pollutions and provides an opportunity for green jobs and research [1, 11, 12].

4 Challenges and Barriers of Implementing Design for Remanufacture

4.1 Economic Considerations and Cost-Effectiveness

There is a misconception that remanufacturing is more expensive than conventional manufacturing. However, this is not the case as the remanufacturer does not need to extract pre-process materials, saving extraction, transportation, and processing energy costs. Some companies design their products in such a way that it is difficult to repair and remanufacture so that they can keep producing and selling new product lines.

Remanufacturers are often perceived as competitors and some original manufacturers go out of their way to design tightly fitted products that are difficult to disassemble to ensure customer keep buying new versions of their products. However, remanufacturing is more cost-effective as original manufacturers could harvest parts from older products, maintaining customer loyalty and saving extraction costs of materials for products.

4.2 Challenges in Design for Remanufacturing

Challenges in design for remanufacturing has to do with the type of product. Products that have high availabilities of cores, stable technology and are in high demand are suitable for remanufacturing. Products with low available cores, rapidly changing technology and low customer demand are more challenging to remanufacture. The remanufactured products need to be sold to a market to be profitable. Cultural perception of remanufactured products as being of lower quality may make it challenging to remanufacture. Stigma in some organizational cultures of circular products make remanufacturing challenging [13, 14]. In the NHS for example, new products may be purchased as opposed to remanufactured products as they are perceived to be of lower risk of being defective than remanufactured medical devices [14]. Overcoming these challenges include awareness raising to build public and organizational support. Companies also need to be educated on the cost-effectiveness and profitability of remanufacturing as well as the impact of sustainability on their businesses.

5 Tools and Approaches for Design for Remanufacture

There is a desperate need for guidelines and frameworks for implementing design for remanufacture [10, 13]. These guidelines are useful for identifying which products will be suitable for remanufacturing. They will also be useful in guiding companies on the process of remanufacturing. Guidelines for design are also important to standardize the remanufacturing process. There is also need for life cycle assessments (LCA) and environmental impact analysis of the remanufacturing process. Although there are theoretical evidences on the cost effectiveness of remanufacturing, companies will be more easily convinced with LCA data demonstrating reduced energy requirements and reduced waste from remanufacturing. This will include goal and scope definition (materials, processes, and products), life cycle inventory analysis (energy/raw materials utilized and waste generated), life cycle impact analysis (environmental impact of remanufacturing inputs and outputs) and interpretation (drawing conclusions from the LCA process to guide decision making) [1, 15, 16].

It is also important that cross-industry knowledge sharing and collaborative design approaches are harnessed in remanufacturing. Lessons can be learnt from medical companies that undertake remanufacturing such as Siemens and Phillips.

6 Future Directions and Opportunities

6.1 Emerging Technologies and Innovations in Design for Remanufacture

There are a lot of emerging technologies that are useful for aiding Design for Remanufacture. These could target each of the six processes for remanufacture. Each of these processes should also be taken into consideration during the design of products to ensure that they can easily be undertaken at the end of life of the product. Some emerging technologies include 3D printing and automated technologies.

6.2 Policy and Regulatory Implications for Promoting Design for Remanufacture and Achieving Net Zero

Business as usual is not an option as Governments are formulating legislation to protect the environment and guide business decisions. Some Governments now require that businesses demonstrate their green credentials for them to win contracts. Following series of environmental action programs, key environmental legislation that guide manufacturing processes have been formulated by the European Union. These are in the form of environmental directives that are implemented by member states in form of regulations. Examples of directives include the End-of-vehicles (ELV) directive for reducing scrapped vehicle waste, the Waste Electrical and Electronic Equipment (WEEE) Directive that encourages circular strategies for electrical/electronic equipment and the Integrated Pollution Prevention and Control (IPPC) Directive for preventing pollution and ensuring prudent use of natural resources [1, 17]. The landfill Directive and Waste Framework Directive are useful legislation for managing waste in the European Union and United Kingdom [18]. There are studies that assume that remanufacturing will help achieve net zero with tools developed to guide decision making, but as suggested earlier, it is important that these assertions are backed with evidence from LCA [19, 20]. There is also work that argue on the importance of remanufacturing among other strategies in achieving net zero, using electric vehicles as case studies [21]. However, further work is needed on the unique role of design for remanufacturing in reducing carbon emissions.

6.3 Potential Collaborations and Partnerships to Drive Design for Remanufacture

In order for design for remanufacture to be embedded in mainstream manufacturing practice, there needs to be greater partnerships/collaboration. These will

include multi-disciplinary partners with the academia, industry, and government. Civil society, non-governmental organizations and the public need to be taken on board in a multi-sectoral intergenerational approach to be effective. There is also need for continued funding to support businesses involved in remanufacture and other circular strategies as well as funding for further research.

7 Conclusion

Design for remanufacture is very important in product design as it takes cognizance of the need to recover and rework a product at the end of its life. With remanufactured products extending product life, reducing waste and greenhouse emissions, design for remanufacture would contribute to zero waste and net zero. There is need for further research for design for remanufacture specific guidelines to guide companies in identifying products suitable for remanufacturing and standardizing the process in such a way that would be cost-effective, safe, and sustainable. The study is a qualitative literature review and all the findings may not be generalized. However, it provides a contribution on the importance of design for remanufacture in achieving net zero and suggests future research directions.

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Product Design Evaluation of Refrigerators to Facilitate Remanufacturing Process



Didik Wahjudi  and Ir Yonatan Yamin

Abstract Remanufacturing is a strategy for processing a product at its end of life. Remanufacturing aims to return a used product or a product that has reached its end of life to the performance and condition of a new product and is equipped with the same new product warranty. Product design is an essential part of a product that increases the remanufacturability of the product. In this study, we discuss how to improve the product design of refrigerators. Refrigerators are white goods products almost every household has. If a refrigerator is not designed to be remanufactured, it will generate a lot of e-waste. This study proposes design improvement of refrigerator products by using the guidelines from design for remanufacturing based on life-cycle thinking. The proposed design improvement considers the product's overall life cycle. With the proposed revision of the refrigerator product design, the refrigerators are expected to be more remanufacturable and produce a more negligible environmental impact.

Keywords Product design · Remanufacturing · Life-cycle thinking · Refrigerator

1 Introduction

The WEEE Forum [1] predicted the growth of e-waste generation by 3–4% annually because of the increasing consumption of electronics, shorter product life cycles, and limited repair options. Remanufacturing has been known for diminishing environmental impacts by reducing virgin materials consumption, consuming less energy, producing less greenhouse gas, and minimizing landfills. However, there are several barriers to materializing these remanufacturing benefits.

White goods are one type of electrical and electronic equipment to be remanufactured [2]. However, the characteristics of white goods that are durable and technologically stable offer a medium potential for growth of remanufacturing [3]. Refrigerator is a type of white goods that increases in number by 2% per year [4]. They predicted there would be 70.7 million units of refrigerators owned by 74.8 million Indonesian

D. Wahjudi (✉) · I. Y. Yamin
Petra Christian University, Surabaya, East Java 60236, Indonesia
e-mail: dwahjudi@petra.ac.id

households in 2030. This vast amount of refrigerator stock will present environmental problems if the end-of-life products are not appropriately handled. In addition, the remanufacturing of refrigerators is rare because of the difficulty of reconditioning and upgrading them to the existing standards [3]. Several studies argue that these barriers can be alleviated by properly designing the product at the early stage [5–7]. This paper aims to improve the remanufacturability of refrigerators by implementing the product design guidelines based on life-cycle thinking developed by Wibowo [8]. The remaining of the paper will be structured as follows. Section 2 discusses literature reviews on the Remanufacturing Process and design for remanufacturing (DfRem) based on life-cycle-thinking. The research methodology of the study is described in Sect. 3. Section 4 provides results and discussions of the findings of this study. Conclusions, limitations, and recommendations for future research are presented in Sect. 5.

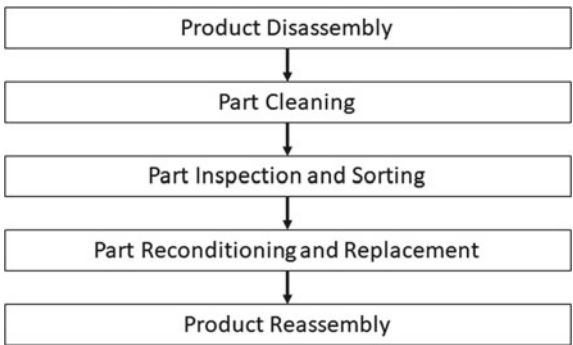
2 Literature Review

2.1 Remanufacturing Process

Remanufacturing is generally conducted in five steps: disassembly, cleaning, inspection and sorting, reconditioning or replacement, and reassembly [9]. Figure 1 shows the five steps of the remanufacturing process.

Before the cores (end-of-life products) are disassembled, they are pre-inspected to assess whether they can be remanufactured. If the cores are deemed appropriate for remanufacturing, they will be disassembled into single parts. Following the disassembly step, every part will be cleaned of dust, dirt, grease, oil, rust, and old paint. Including all kinds of cleaning methods at this step, such as using petrol, hot water jet or steam cleaning, chemical detergent spraying or soaking, ultrasonic cleaning, sand-blasting, and steel brushing, is prevalent. These various cleaning technologies and processes can be used sequentially or simultaneously. This cleaning result depends

Fig. 1 The five steps of the remanufacturing process



on chemical agent concentration, heat effect, mechanical exposure, and process time [9]. It is advised to utilize water, steam, and water-soluble detergents as much as possible as the primary cleaning agents to protect components and the environment.

The next step of the remanufacturing process is to inspect and sort every part. Inspection and sorting are mainly conducted visually. Besides that, mechanical and electronic inspection procedures such as leak tests, voltage tests, and three-dimensional measurements are often used. The inspection will determine whether the parts are reusable without reconditioning, reusable after proper reconditioning, or not reusable [9].

The fourth step in the remanufacturing process is reconditioning worn-out parts and replacing the nonreusable ones. It is the most critical stage in the remanufacturing operations that sometimes takes up one-half of the remanufacturing area. Parts undergo several machining processes and sometimes a heat treatment at this step. Through the machining processes, the parts' geometrical dimensions change. However, the original tolerances must be maintained so as not to affect the products' performance. The reconditioning process returns the parts to a like new condition, where the customer cannot distinguish between a new and a remanufactured one [9]. On the other hand, if a part is not reusable, a replacement part, either a new or remanufactured one, will replace it. That is why it is a common practice to have a larger number of cores than the number of remanufactured products to be assembled.

In the last step, the remanufactured products are reassembled using the same tools and equipment used in the new product assembly process. However, unlike the inspection of the new products conducted randomly, the remanufactured products undergo 100% functional inspection and test run. It makes the remanufactured products more reliable than the new products [9].

2.2 Design for Remanufacturing (DfRem) Based on Life-Cycle-Thinking

Several studies have developed design for remanufacturing (DfRem) guidelines to improve the remanufacturability of products [6, 7, 10, 11]. DfRem includes design for assembly, design for disassembly, design for the core collection, design for multi-life cycles, design for upgradation, and design for evaluation [10]. Sundin and Lindahl [12] improved the design of forklift trucks, soil compactors, household appliances, and single-use cameras to facilitate integrated product service offerings. Wang, Liu [13] used modular design to facilitate the design for disassembly and remanufacturing of machine tools. Yang, Nasr [14] applied DfRem principles to select the materials for two automotive parts, namely engine block and intake manifold, making the two parts easier for remanufacturing.

Pigosso, Zanette [15] argued the importance of considering the whole product life cycle during the early design stage. Therefore, Wibowo [8] developed a design

for remanufacturing guidelines based on life-cycle thinking. These guidelines classify a product's life cycle into five stages: raw material extraction and processing, product manufacturing, packaging and distribution, product use, and end-of-life (EoL) management.

The product design for the raw material extraction and processing stage aims to reduce the use of non-renewable materials and increase the efficiency of material use [8]. Practices that support these objectives include increasing the use of renewable and recycled materials, reducing the use of materials that require large amounts of energy to manufacture, and reducing the products' dimensions, weight, and number of components.

The product design for the manufacturing stage focuses on reducing the production process's adverse effects and improving the assembly process's efficiency. Properly designing the products can decrease hazardous waste generated during the production process.

The product design for the packaging and distribution stage emphasizes minimizing the packaging material requirement and improving the efficiency of product handling, storage, and transportation.

The product design for product use stage aims to extend product usage, reducing the products' energy consumption and improving their ease of use and maintenance.

The product design for end of life management stage focuses on improving the products' remanufacturability in disassembly, cleaning, inspection and sorting, reconditioning, and reassembly [8].

3 Research Methodology

This study began with studying the life-cycle-thinking-based design for remanufacturing guidelines. It is essential to comprehend the essence of the guidelines to be aware of the advantages and disadvantages of the existing refrigerator designs. The next thing was to acquire end-of-life refrigerators to be studied. Three cores were studied in this research: the Sharp SJ-017-SL model, the Samsung SR-24NME model, and the Toshiba GR-EF37-W model. All of them were two-door refrigerators with a minimum age of ten years. The three refrigerators were disassembled one by one. All events during disassembly were recorded. The last step was identifying which guideline criteria can be applied to improve the existing design. A comparison analysis was conducted to obtain a big picture of the similarities and dissimilarities of the existing refrigerator designs.

4 Results and Discussions

The author observed the following events during the disassembly process: copper pipe needs to be cut, rusty bolts, and a broken defrost heater. Table 1 compares the advantages and disadvantages of the three refrigerator models during the disassembly process. Figure 2 shows the front view of the Toshiba refrigerator’s freezer section. There are many cable connectors on this refrigerator. After finishing the disassembly process on the three refrigerator models, we inspected the condition of the parts. Figure 3 presents the condition of parts at the rear side of Toshiba refrigerators. Many rusty components needed to be checked and reconditioned. Table 2 lists parts that can be reused as is, must be reconditioned and must be replaced. From Table 2, it can be seen that most parts are to be reconditioned. Only a few parts are reusable as is. The objective of remanufacturing is to have as many as possible parts that can be reused and to minimize the number of parts that need to be replaced. Given that objective and considering the life-cycle-thinking of refrigerators, the following recommendations are obtained. Table 3 provides the recommendation list, the reasons for these recommendations, and the related life cycle stage.

Most of the recommendations mentioned above are to improve the remanufacturability of the product, namely making it easier for cleaning, disassembly, reconditioning, and reassembly. The following recommendation section is to extend the product life: early warning on damaged components, ease of maintenance and repair, protection on the most valuable part, and potential for performance upgrade. The last recommendation section is to reduce the environmental impact, namely improving the recyclability of parts.

Out of the five product’s life cycle stages, namely raw material extraction and processing (RawMat), product manufacturing (ProMan), packaging and distribution (Pack), product use (ProUse), and end-of-life management (EoLMan), this study

Table 1 Comparison of the disassembly process on three refrigerator models

	Sharp SJ-017-SL	Samsung SR-24NME	Toshiba GR-EF37-W
Advantages	– Easy to reach the fasteners – No fasteners on the evaporator – Few cable connectors – Only one cable outlet – No rusty fastener	– No fasteners on the case – Few cable connectors	– No fasteners on the case
Disadvantages	– Need to cut copper pipe that connects evaporator to compressor	– Need to cut copper pipe that connects evaporator to compressor – Rusty fasteners on the case and evaporator	– Need to cut copper pipe that connects evaporator to compressor – Rusty fasteners on the compressor – Many cable connectors

Fig. 2 Front view of the refrigerator's freezer section

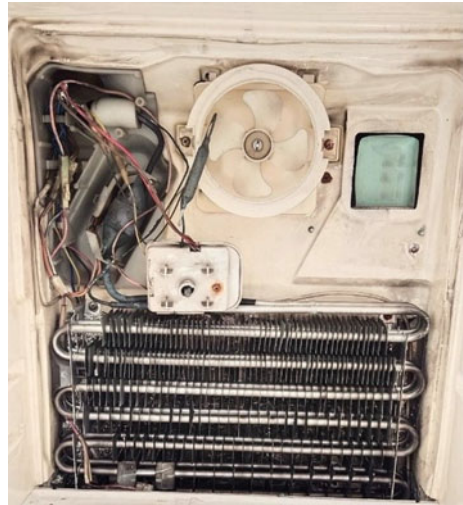


Fig. 3 Rear side of Toshiba refrigerator



provides recommendations of four stages of the product life cycle. The limited information on how the products are packaged and distributed makes it challenging to offer recommendations on this life cycle stage.

One characteristic of remanufacturing is the ability to upgrade the product to match the capabilities of the latest version. Modular design can facilitate this purpose, as suggested by [13]. Refrigerators can upgrade the following parts to make them more energy efficient: compressors, evaporator and condenser fans, motors, door face frame and casket design, defrost technology, and insulations [16]. However, Boustani, Sahni [16] argue that the energy savings resulting from the remanufacturing may not justify it if the newer technology can save more energy. Therefore, it is essential to design a refrigerator that allows its components to be replaced with components with newer technology.

Table 2 List of parts that can be reused as is, must be reconditioned, and must be replaced

Parts	Reusable as is	Reconditioned	Replaced	Remarks
Main body		✓		
Doors		✓		
Fasteners			✓	Check, replace if it rusts
Door rubber seal			✓	Check, replace if the rubber is stiff
Shelves	✓			
Drip pan		✓		
Wiring cable			✓	Check, replace if the cable is cut
Cable connectors	✓			
Inner case		✓		
Bulb	✓			Check, replace if the bulb is broken
Thermostat		✓		
Fan		✓		
Evaporator		✓		
Compressor		✓		
Copper pipe			✓	Check, replace if the pipe is leaking or cut
Defrost heater		✓		
Powerbox		✓		

5 Conclusions

Remanufacturing of refrigerators is still rare. One way to improve the potential of refrigerator remanufacturing is to improve their product design. This study aims to provide design recommendations for refrigerators based on the life-cycle-thinking consideration. This research was conducted by disassembling three cores of two-door refrigerators from different brands.

This study proposes twelve improvements. These twelve recommendations are related to raw material extraction and processing, product manufacturing, product use, and end-of-life management stages of the product life cycle. Implementing these recommendations will not only make the product easier to remanufacture, but also it will have less environmental impact.

The recommendation for future research is to involve refrigerator manufacturers to obtain additional information on what problems the refrigerator often experiences and to confirm the feasibility of the proposed design improvements to be implemented. Furthermore, it is advisable to perform a life cycle analysis to assess the feasibility of replacing older components with more energy-efficient ones as part of the specification upgrade.

Table 3 Design recommendation after implementing life-cycle-thinking-based guidelines

No.	Recommendation	Reason	Life cycle stage
1	Use of recyclable or biodegradable plastic as much as possible for all parts	Reducing environmental impact	EoLMan
2	Providing a coverable hole on the freezer base to make it easier to reach the defrost heater	Making it easier for assembly, disassembly, and reassembly	ProMan, EoLMan
3	Providing the temperature sensor to monitor the refrigerator's performance	An early warning if any component is damaged	ProUse
4	Providing a sign or information on how to open a cover	Reducing damage potential due to wrong handling	ProUse, EoLMan
5	Providing barcode or QR code on how to do total disassembly	Reducing the potential for errors during routine maintenance, repair, or remanufacturing	ProUse, EoLMan
6	Providing coding or markings on parts	Making it easier for recycling and other end-of-life management purposes	EoLMan
7	Providing enough space between fasteners and other parts	Making it easier and faster for disassembly	EoLMan
8	Providing better connecting joints between the copper pipe and the compressor, evaporator, and defrost heater	Reducing the potential for damage to the copper pipe, compressor, evaporator, and defrost heater	EoLMan
9	Using a more corrosion-resistant fastener	Making it easier and faster for disassembly and improving the reusability of the fasteners	RawMat, EoLMan
10	Using fewer cable connectors	Making it easier for assembly, disassembly, and reassembly and reducing the potential for errors	ProMan, EoLMan
11	Providing a corrosion-resistant coating and protecting cover on the compressor	Protecting the compressor (the most valuable part of a refrigerator) and making it easier for cleaning and reconditioning	RawMat, ProUse, EoLMan
12	Utilizing modular design	Making it easier for disassembly and performance upgrade	RawMat, EoLMan

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Modelling Remanufacturing Process of End-of-Life Batteries Using Discrete Event Simulation



Michael S. Packianather, Felisa A. Zainuddin, Anthony Soroka,
Peter Tuthill, and Eva Ames

Abstract This paper focuses on developing a Discrete Event Simulation (DES) model using WITNESS for the process of remanufacturing End of Life (EoL) batteries. This study shows how the DES model could be used to understand the dynamics of the process flow for identifying the bottlenecks and finding feasible solutions based on Fit Remanufacturing principles in order to improve the performance of the whole remanufacturing process. The DES model was run using an iterative process to reduce idle times, increase utilisation times and minimize blockages and waiting times for the processes involved leading to an increase in the throughput of remanufactured battery packs/day from 10 to 30 after four weeks of continuous operation. Further, the blockage times were eliminated and reduced to less than 4% in all but two machines used in the remanufacturing of EoL batteries.

Keywords Remanufacturing · Fit remanufacturing · Discrete event simulation

1 Introduction

A global transport and logistics company has initiated a project to manage retired lithium-ion batteries from shared electromobility scooters provided by one of their clients that focuses on providing shared micro mobility electric scooters in urban areas as a part of sustainable alternatives to cars. As a part of their Climate Action Plan, one of the many solutions proposed is the reuse of the retired lithium-ion batteries in second life applications to extend their lifespan. It is worth noting that when Electric Batteries (EV) reach their End of Life (EoL) typically they will have

M. S. Packianather (✉) · A. Soroka
School of Engineering, Cardiff University, Cardiff CF24 3AA, UK
e-mail: PackianatherMS@cardiff.ac.uk

F. A. Zainuddin
Environment and Climate Change, Islington Town Hall, Upper Street, London N1 2UD, UK

P. Tuthill · E. Ames
DSV, Parkeston, Harwich CO12 4QG, UK

80% of their capacity remaining in them which means they can still be used for less demanding stationary applications. This study explores the EoL battery solutions through Discrete Event Simulation (DES) modelling using a software package called WITNESS developed by Lanner. Once the DES model is developed it can be simulated and run many times to study the process flow during remanufacturing so that it could be made more efficient through identifying the causes of bottlenecks and then eliminating or reducing them one by one. This is done by incorporating the concept of Fit Remanufacturing in terms of introducing lean remanufacturing, agile remanufacturing and sustainable remanufacturing into the process pathways of remanufacturing EoL lithium-ion batteries.

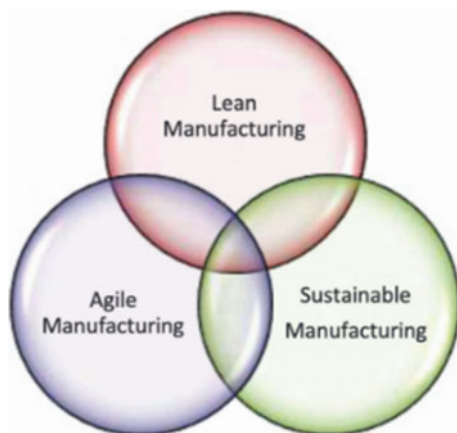
This paper is organized as follows. The Fit Remanufacturing concept is introduced in Sect. 2. In Sect. 3 the development of the Discrete Event Simulation (DES) model using WITNESS for the remanufacturing of EoL batteries is explained. The results of running the initial DES model for the identification of bottlenecks and how they could be resolved by implementing feasible solution and the verification of these modifications to the model are presented in Sect. 4. Section 5 concludes this study.

2 Fit Remanufacturing

Manufacturing systems began to evolve during the early 1900s. The evolution began with the concept of mass production, which then advanced into economic and agile production. From this revolution during the 20th Century different manufacturing concepts have emerged including Fit Manufacturing Framework (FMF) [10]. Fit Manufacturing (FM) generally is the combination of Lean Manufacturing (LM), Agile Manufacturing (AM) and Sustainable Manufacturing (SM) (Ebrahim, 2011) as illustrated in Fig. 1. The term “fit” itself targets a holistic overall manufacturing solution to problems such as high instability of the market and complicated manufacturing environment [4]. The benefits of implementing FM include capability to cope quickly to the markets and demands that can be highly volatile, provide a long-term strategy for continuous improvement and value creation, provide optimum settings to maximise economic benefits and to improve production processes to become more environmentally sustainable [11].

In order to implement FM, it is important to understand the basics of the three manufacturing strategies involved. Lean strategy has been introduced in the manufacturing sector starting back in the industrial revolution [8]. The concept of Lean Manufacturing (LM) aims to exclude any unnecessary processes and actions that do not create any value to the end product of the manufacturing system. This is considered a strategy that involves waste elimination within the manufacturing system.

Fig. 1 Elements of fit manufacturing [11]



The concept of Agile Manufacturing (AM) is mostly driven by the market volatility caused by factors such as globalisation, adjustments on customer needs and best practice development [6]. In AM, it is vital to note that process tools, modular systems that can be reconfigured, and training for employers are required for fast response to any market disruption while maintaining the cost and quality of manufacturing [7].

Incorporating sustainability into the agile and lean manufacturing make the Fit Manufacturing complete. The basic understanding of sustainability is that it is a concept that covers three main interrelated elements which are the environmental, social and economical in nature. Hence, sustainability in manufacturing systems is the manufacturing of products by utilising clean processes and non-polluting equipment, natural resources and conservation of energy while also being financially feasible and not dangerous for the workers, customers and the communities [4].

In this study, FM is applied in the context of remanufacturing and is called Fit Remanufacturing (FR) with Lean Remanufacturing (LR), Agile Remanufacturing (AR) and Sustainable Remanufacturing (SR) as its key components to achieve the same outcomes both in manufacturing as well as in remanufacturing [3].

3 Discrete Event Simulation Model for Fit Remanufacturing

In this section the development of a Discrete Event Simulation (DES) model using WITNESS Horizon [9] for the remanufacturing of End of Life (EoL) batteries will be described. The assumptions made in this study and the process flow mapping used to create the DES model will also be given in the following sections.

3.1 Assumptions

There are several key assumptions that were made during the development of the DES model. The assumptions are as follows:

- The retired battery packs sent to the EoL battery remanufacturing plant are all of the same design, size and specifications;
- The EoL battery packs used in the simulation are the 85kWh rated Tesla Model S battery packs;
- Shifts are not considered for the staffs and labours at the manufacturing plant;
- The EoL life battery remanufacturing plant operates 24 h, every single day for the whole year (365 days) without any breakdowns;
- Approximately 5% of the batteries are either physically damaged or leaked;
- Other battery components such as the Battery Management System and wires are not considered the remanufacturing process;
- Maintenance of machines are not considered;
- Cost of new lithium-ion batteries are \$132/kWh [1],
- The cost of a repurposed battery is considered 70% of a new battery;
- Time taken to discharge the battery prior to visual inspection was not considered;
- Assume 5% directly recycled [5],
- The battery packs are from the EVs in the United Kingdom.

3.2 Process Flow Mapping

A simulation model requires useful and accurate information as input parameters to ensure that the characteristics of the model is close to the real life situations. This can be done by initially creating a process flow map of the system, which is a tool used to visually illustrate the detailed course of action of a work activity. By building a process flow map, it is also possible to recognise the data needed and the interaction between the element processes. Every element in the system is represented by flowchart shapes.

In this study, the process flow map aims to identify the key activities in EoL battery remanufacturing, the sequence and the way in which these activities interact with each other. Before building the simulation model, the key activities for the EoL battery remanufacturing were identified from the literature. The initial workflow of the remanufacturing process with the identified main key activities of the process were created and is shown in Fig. 2.

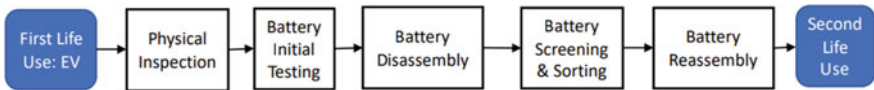


Fig. 2 An initial process flow of end of life batteries

As shown in Fig. 2, after the EV batteries reach their EoL in which their capacity has reached 80% of its nominal capacity, the batteries are sent for visual inspection to check for any indication of physical damage. Afterwards, the battery packs are tested before being disassembled into battery cells or modules. The battery cells and battery modules are tested and sorted accordingly before being reassembled back into battery packs, ready for their second life use. Both the input and output of this process flow are battery packs of similar size and configurations. With further findings from the literature review, the battery disassembly can be expanded further, either at module levels or cell levels. This is shown in Fig. 3 where the arrows with different colours represent different battery types (packs, modules or cells). The cut-off values for each route is given in Table 1.

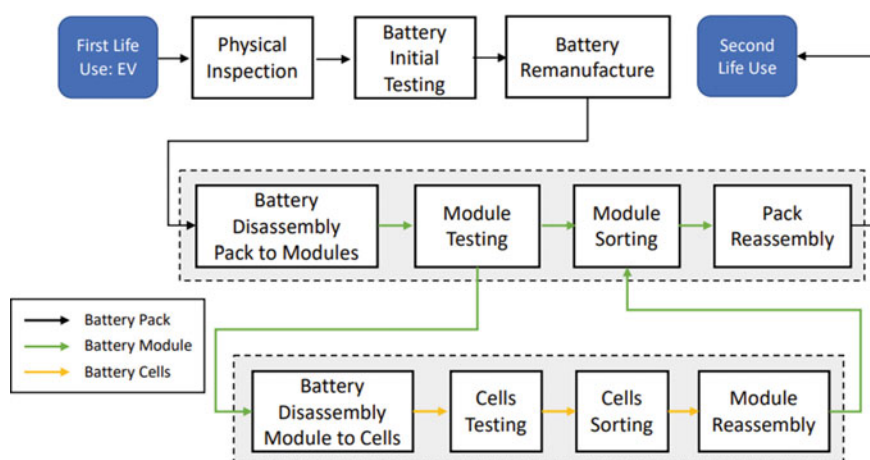


Fig. 3 Expanded process flow of end of life batteries remanufacturing with different levels of battery disassembly

Table 1 Output decision for different processes

Process	Outcome	Decision
Physical inspection	Damaged	Battery recycling
	Not damaged	Battery initial testing
Battery pack initial testing	SOH > 90%	Direct reuse as spare parts
	90% > SOH > 80%	Direct repurpose
	SOH < 80%	Disassembly into battery modules
Battery modules testing	SOH > 80%	Modules sorting
	SOH < 80%	Disassembly in battery cells
Battery cells testing	SOH > 50%	Cells sorting
	SOH < 80%	Battery recycling

Table 2 Parts and attributes used in the discrete event simulation (DES) model

EoL_Batt_Pack 	Attr_SOH_Pack = TNormal(0.75, 0.15, 0.05, 0.99)	The end of life EV battery packs with 80% of its nominal
Batt_Module 	Attr_SOH_Module = TNormal(0.75, 0.20, 0.05, 0.99)	Battery modules extracted from end of life EV battery packs
Batt_Cells 	Attr_SOH_Cells = TNormal(0.75, 0.25, 0.05, 0.95)	Battery cells extracted from end of life EV battery packs

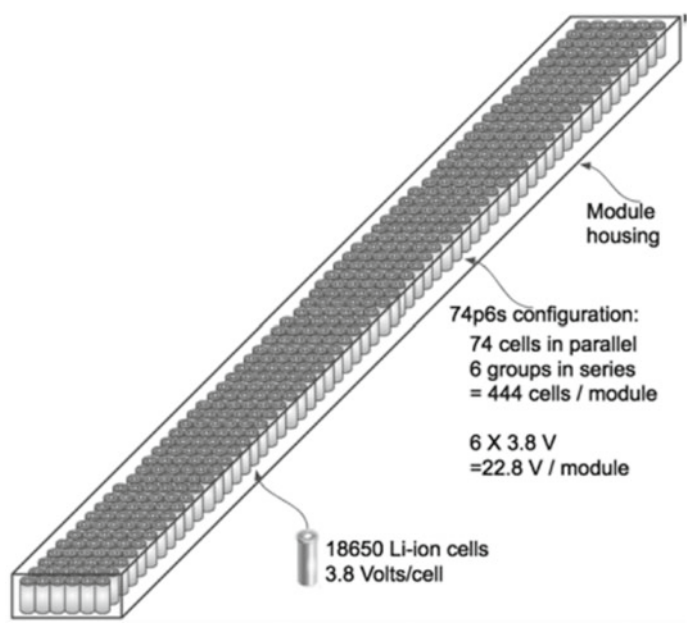


Fig. 5 Cells configuration in a tesla model S battery module [12]

Station. For this study, only the Single, Batch, Assembly and Production elements are utilised. Each of the machines are connected to one another through the use of Conveyors. This element is used to transport the battery packs, modules and cells. Furthermore, the number of Labours for each machine are given in Table 3. Generally, the number of Labours allocated depends on the type of work undertaken by each station and the type of machine used. The machines can be either manual, automated or hybrid.

Table 3 Number of labours and automation levels of each machine

Machine name	Number of labours	Level of machine automation
<i>Physical_Inspection</i>	1	Manual
<i>Initial_Testing</i>	2	Manual
<i>Pack_Disassembly</i>	2	Manual
<i>Module_Testing</i>	1	Manual
<i>Module_Disassembly</i>	2	Manual
<i>Cells_Testing</i>	2	Manual
<i>Cells_Sorting</i>	N/A	Automated
<i>Module_Reassembly</i>	1	Hybrid
<i>Module_Sorting</i>	N/A	Automated
<i>Pack_Assembly</i>	2	Automated
<i>Final_Inspection</i>	1	Manual

Each of the element in the remanufacturing plant is defined with different process times as given in Table 4. This was estimated based on the findings from the literature.

The process times in Table 4 is based on the assumption in which the EoL batteries are reassembled into similar pack configurations as per the arriving EoL battery packs ($444 \text{ cells} \times 16 \text{ modules per pack}$). However, the process times will be different if the reassembled batteries have different pack configurations (eg. $150 \text{ cells} \times 8 \text{ modules per pack}$).

Using the elements and data as stated above the DES model was developed as shown in Fig. 6. The red arrows indicate the flow of the parts going through the machine elements. Each of the machines modelled require an input and output rule to ensure smooth flow of battery packs, modules and cells within the system.

Table 4 Process time for each machine

Element name	Process time (min)	Notes
<i>Physical_Inspection</i>	60	—
<i>Initial_Testing</i>	370	—
<i>Pack_Disassembly</i>	300	Rough estimation from video
<i>Module_Testing</i>	10	10 min of testing per module, including set up time
<i>Module_Disassembly</i>	180	Rough estimation from video
<i>Cells_Testing</i>	32	2 min per test with 30 min set up time
<i>Cells_Sorting</i>	10	Educated estimate
<i>Module_Reassembly</i>	36	4.8 s/cell
<i>Module_Sorting</i>	5	Educated estimate
<i>Pack_Assembly</i>	20	20 min/pack
<i>Final_Inspection</i>	60	—

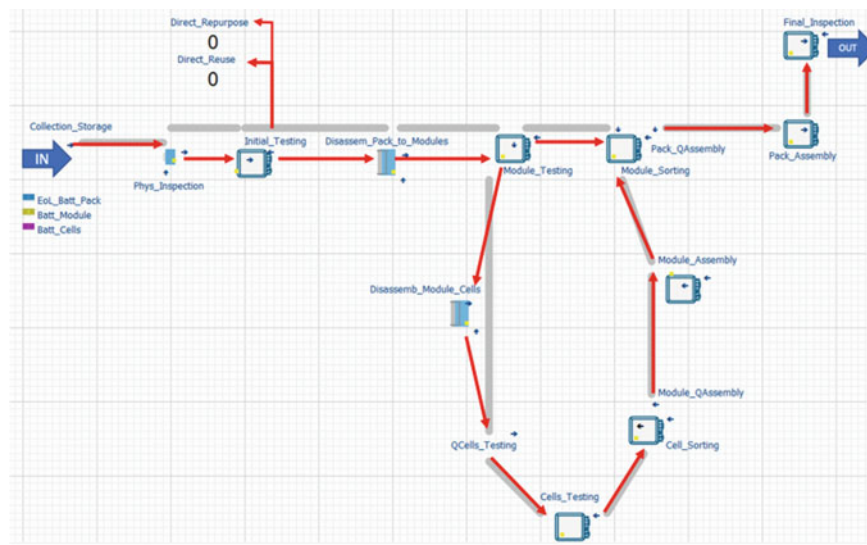


Fig. 6 The DES model for remanufacturing and repurposing EoL batteries

4 Results of Running the Discrete Event Simulation Model

The DES model was run for a duration of one week, two weeks and four weeks. In order to be more efficient and highly productive, some adjustments were made for reducing the bottlenecks within the remanufacturing process flow by making it more lean, agile and sustainable according to the Fit Remanufacturing paradigm.

4.1 Identifying the Bottlenecks in the Initial DES Model

The states of the machine over the simulation period of one, two and four weeks are shown in Fig. 7 (green—idle; blue—busy; purple—blocked) and the percentage of blockage time of the machines are recorded in Table 5. The number of shipped battery packs was found to be 10 after the four weeks duration.

According to Fig. 7, the cells sorting, module sorting and pack assembly stations are idle majority of the time. For cells and modules sorting, this is due to the large minimum batch that was required to be filled before processing the parts. Hence, most of the time during the simulation period, the sorting machines are waiting for the parts to fill up the batch capacity. This could be reduced by increasing the rate in which parts are going into the sorting machines or reducing the number of minimum batch size for the sorting machine. However, the latter suggestion would compromise the homogeneity of the battery cells SOH across the battery module and battery pack. Hence, the former suggestion would be a more sustainable solution. Furthermore,

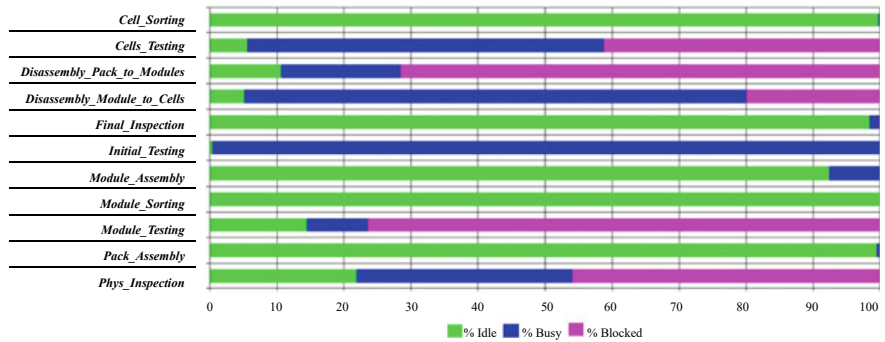


Fig. 7 States of the machines in the initial DES model

Table 5 The % of blockage time in the initial DES Model after 1, 2 and 4 weeks

Machine	Week 1 (%)	Week 2 (%)	Week 4 (%)
<i>Cell_Sorting</i>	0.0	0.0	0.0
<i>Cells_Testing</i>	31.9	37.3	41.2
<i>Pack_Disassembly</i>	15.9	52.9	71.5
<i>Module_Disassembly</i>	0.0	6.7	19.9
<i>Final_Inspection</i>	0.0	0.0	0.0
<i>Initial_Testing</i>	0.0	0.0	0.0
<i>Module_Reassembly</i>	0.0	0.0	0.0
<i>Module_Sorting</i>	0.0	0.0	0.0
<i>Module_Testing</i>	22.7	57.9	76.4
<i>Pack_Reassembly</i>	0.0	0.0	0.0
<i>Phys_Inspection</i>	0.0	9.6	46.0

reducing the blockage from downstream processes can also increase the throughput of the process and make the whole remanufacturing system more productive and efficient. This is discussed in the following sub-section.

4.2 Validating the Modified DES Model

Based on Table 5, the obvious bottlenecks after four weeks of simulation are detected at Physical Inspection (46.0%), Module Testing (76.4%), Pack Disassembly (71.5%), Cells Testing (41.2%) and Module Disassembly (19.9%). As one of the earliest stage in the whole process, the physical inspection bottleneck could be improved by increasing the number of initial testing station. This modification is referred to as Modification 1 (M1). The results of M1 showed a decrease in the physical inspection station bottleneck as the blockage time reduced to 0%. However, this

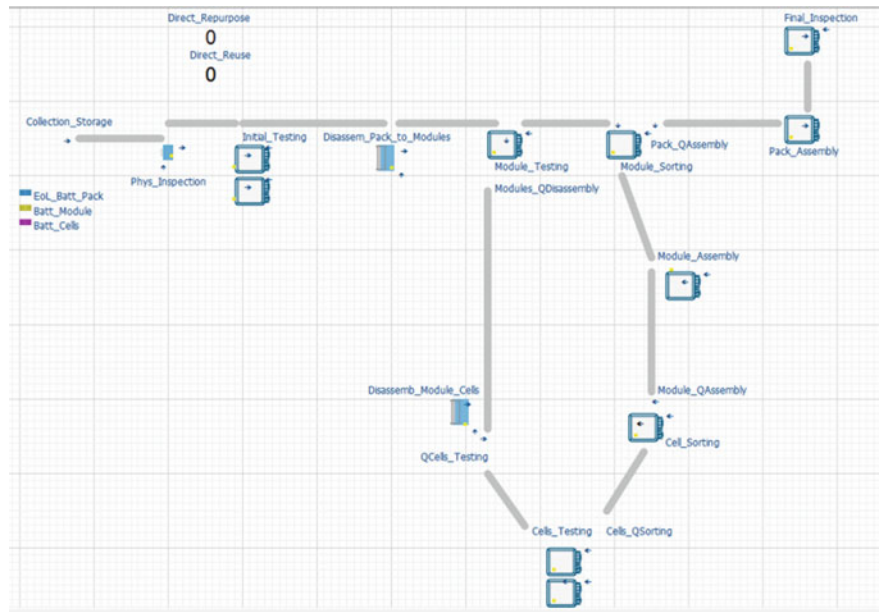


Fig. 8 The modified DES model for remanufacturing EoL batteries

caused the blockages in other stations such as Initial Testing, Pack Assembly and Pack Disassembly to increase. As the output of the physical inspection increased due to increase in the number of stations, this caused the downstream process to experience surge at the input. The initial testing for battery packs, module testing and module disassembly bottlenecks were relieved by adding a buffer after the module testing process. A buffer is considered as a storage between machines, that is used to avoid any machine failures from affecting the whole remanufacturing line. This change is referred to as Modification 2 (M2).

With M2 implemented, the blocks at the pack disassembly, initial testing, and module testing were reduced significantly. However, this did not include the module assembly and cells testing machines. Hence, to improve the bottleneck at the module disassembly, either the buffer capacity at the queue after module disassembly should be increased or the number of cells testing machines should be increased. While increasing the buffer capacity would be cheaper, increasing the number of machines, though expensive would be able to increase the throughput to 30 battery packs/day. This is referred to as Modification 3 (M3). As predicted, M3 improved the module disassembly bottlenecks as well as increasing the throughput to 30. An increase in the throughput indicates that the manufacturing flow has improved. Therefore, Modification 4 (M4) was then executed to reduce the bottlenecks that the cell testing machines were experiencing, in which a buffer was introduced after the cell testing stations. The DES model after modifications M1, M2, M3 and M4 is shown in Fig. 8 and the resulting machine states are depicted in Fig. 9.

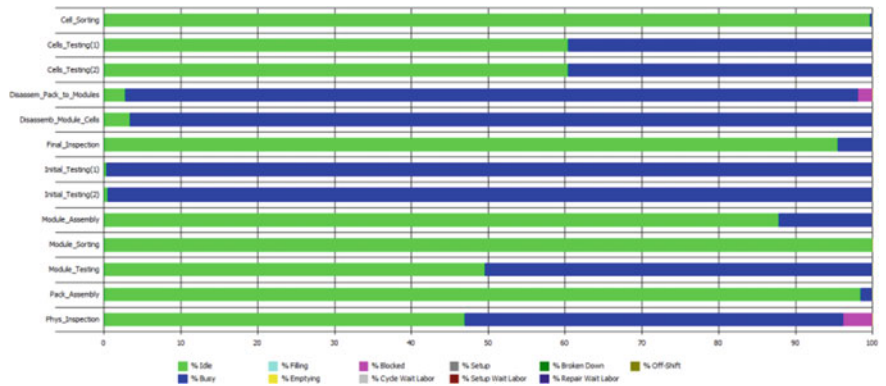


Fig. 9 The improved states of the machines in the modified DES Model

Table 6 The % of blockage time in the modified DES Model

Machine	Week 1 (%)	Week 2	Week 4
<i>Cell_Sorting</i>	0.0	0.0	0.0
<i>Cells_Testing</i> × 2	0.0	0.0	0.0
<i>Pack_Disassembly</i>	1.7	1.8	1.9
<i>Module_Disassembly</i>	0.0	0.0	0.0
<i>Final_Inspection</i>	0.0	0.0	0.0
<i>Initial_Testing</i> × 2	0.0	0.0	0.0
<i>Module_Assembly</i>	0.0	0.0	0.0
<i>Module_Sorting</i>	0.0	0.0	0.0
<i>Module_Testing</i>	0.0	0.0	0.0
<i>Pack_Assembly</i>	0.0	0.0	0.0
<i>Phys_Inspection</i>	0.0	0.0	3.8

The new results shown in Table 6 indicate that the only bottleneck that exists in the remanufacturing line is the pack disassembly and physical inspection. However, the current blockage time is considered to be minimal.

5 Conclusions

In this study a Discrete Event Simulation (DES) model for remanufacturing of End of Life (EoL) batteries has been developed using WITNESS. The initial DES model has been used successfully for identifying bottlenecks in the remanufacturing process. Some modifications based on Fit Remanufacturing paradigm have been implemented. The modified DES model has been validated and the results showed an increase in the number of remanufactured battery packs/day from 10 to 30 after

four weeks of continuous operation. Further, the % of blockage times have been eliminated and reduced to less than 4% in all but two machines. Future work will focus on optimising the remanufacturing process of EoL batteries.

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An Analysis of Dual Peg-Hole Disassembly Problems



Farzaneh Goli , Yongquan Zhang , Yongjing Wang ,
and Mozafar Saadat

Abstract The disassembly process plays a key role in remanufacturing. The paper presents a systematic evaluation of the various contact states that can occur during the extraction a dual-peg from a dual-hole (ie. the dual peg-hole disassembly problem), with a particular emphasis on the problem of jamming that arises in two-point contact states. This paper shows the geometrical and quasi-static analyses, simulations, and boundary conditions of the two-point contact states.

Keywords Dual peg-hole extraction · Disassembly · Active compliance centre · Robotic · Force analysis · Jamming

1 Introduction

Management of end-of-life (EOL) products is a global challenge because their disposal can have a significant impact on both the environment and the economy [1]. A solution to this issue is the recycling, reuse, and remanufacturing of these products. This approach enables their components and materials to be separated in a non-destructive manner, preserving them for future use. Disassembly is a crucial step in the remanufacturing process as it connects the return of a product to its recovery. To improve the efficiency of disassembly, automatic disassembly using robots has been proposed. One common task in disassembly is extracting a peg from a hole

F. Goli (✉) · Y. Wang · M. Saadat
Mechanical Engineering Department, University of Birmingham, Birmingham, UK
e-mail: Fxg174@student.bham.ac.uk

Y. Wang
e-mail: y.wang@bham.ac.uk

M. Saadat
e-mail: m.saadat@bham.ac.uk

Y. Zhang
Mechanical Engineering Department, Wuhan University of Technology, Wuhan, China
e-mail: zhangyongquan@whut.edu.cn

with clearance fit. The geometry characteristics of components play a crucial role in determining their interactions during assembly and disassembly. Specifically, the geometries of the parts can significantly impact disassembly, as lateral and angular misalignment between separated components can result in an increase in reaction forces, presenting a significant challenge. Furthermore, forces acting on the robot can cause the robotic system to become stuck or jammed during extraction.

Jamming and wedging during the disassembly process can cause difficulties and severe damage to the components and robots [2]. While Whitney et al. analysed the quasi-static assembly of a cylindrical peg into a chamfered hole [3], these issues have been resolved using industrial robots and compliance strategies such as the Remote Compliance Centre (RCC) [4]. Numerous studies have been conducted on peg-hole assemblies using compliant manipulators. For example, Simunovic and Whitney developed an RCC device to enhance peg-hole insertion efficiency [5]. They analysed the insertion of rectangular pegs without chamfer and a three-dimensional rectangular peg insertion.

Yongquan et al. conducted a quasi-static analysis of peg-hole disassembly using a compliance device, exploring factors such as degree of compliance, compliance centre location, and position error [4]. Wang et al. contrasted passive and active compliance, with the latter proving to be more advantageous due to its faster dynamic response, despite associated higher costs and limited speed of response [6]. Despite these drawbacks, active compliance is an effective approach to enhance assembly reliability [7]. Several researchers, including Sathirakul and Fei [8], have utilised the compliance principle in multi-peg-hole assembly tasks to rectify lateral and angular misalignments, demonstrating that active compliance can enhance assembly reliability.

The current study aims to perform a jamming analysis of dual peg-hole extraction problems in two dimensions. The next sections of the paper are organised as follows: Section II analyses multiple peg extraction during disassembly, Section III provides a geometric analysis of dual-peg extraction, and Section IV describes the force analysis of dual-peg extraction.

2 Analysing the Extraction of Dual Pegs During Disassembly

The dual peg-hole extraction procedure involves the simultaneous removal of two pegs from their respective holes (Fig. 1). Although it is a three-dimensional problem, it can be simplified and represented in two dimensions, as discussed by Byoung-Ho et al. [9]. In this analysis, the pegs are considered rigid and have equal lengths, and the extraction is only in a vertical and upward direction. The active compliance centre is assumed to be positioned along the extraction axis and between the two holes.

By making these assumptions, the forces and moments generated by the interaction between pegs and holes can be calculated. This prediction of forces and torques

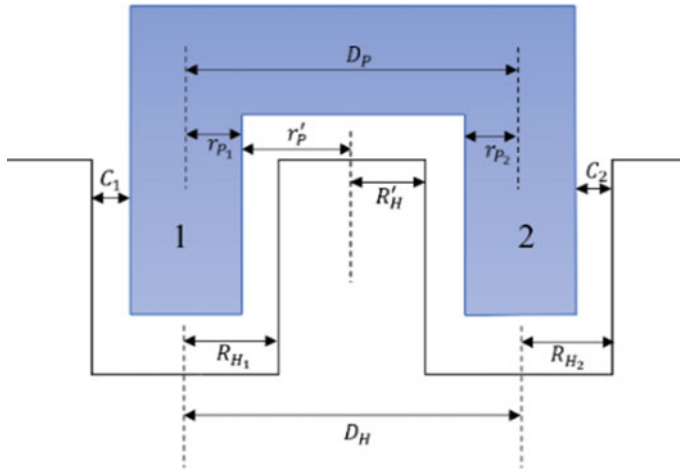


Fig. 1 The geometric model of a dual peg-hole

can help identify the configurations where the compliance devices supporting the pegs (such as the Remote Centre Compliance, Spatial RCC, or Active Compliance Centre) may fail to prevent jamming and wedging [10]. This force/torque analysis provides a deeper insight into the physics of dual peg-hole extractions that use compliance mechanisms. In a dual peg-hole scenario, utilization of an active compliance centre is expected to lead to a successful extraction if the initial configuration is correct. The extraction phase of the dual peg-hole extraction problem will be extensively examined in the subsequent sections.

3 Dual-Peg Extraction Geometric Analysis

3.1 Capacity for Extraction

Figure 1 shows dimensions of a dual peg-hole. The radius of peg 1 (r_{P_1}) and peg 2 (r_{P_2}) are distinct, as are the radius of the first hole (R_{H_1}) and the second hole (R_{H_2}). D_P is the spacing between the centres of the pegs, and D_H is spacing between the centres of the holes. The distance from the first peg to the first hole is represented by C_1 , and the distance from the second peg to the second hole is represented by C_2 . The extraction depth is represented by h .

To facilitate a clear understanding of the dual peg-hole disassembly problem, it is necessary to consider the following conditions that constrain the process:

- (a) The pegs must be smaller than the corresponding holes, thus:

$$r_{P_1} < R_{H_1}, \text{ and } r_{P_2} < R_{H_2} \quad (1)$$

- (b) The distance between the outer edges of the pegs must be less than the distance between the outer edges of the holes, it can be written:

$$D_P + r_{P_1} + r_{P_2} < D_H + R_{H_1} + R_{H_2} \quad (2)$$

- (c) The distance between the inner edges of the pegs must be greater than the distance between the inner edges of the holes, which can be expressed as:

$$D_P - r_{P_1} - r_{P_2} > D_H - R_{H_1} - R_{H_2} \quad (3)$$

The above conditions can be combined and expressed as:

$-C_1 + C_2 < D_H + D_P < C_1 + C_2$, where C_1 and C_2 are the clearances and are defined as: $C_1 = R_{H_1} - r_{P_1}$ and $C_2 = R_{H_2} - r_{P_2}$.

The ability of pegs to be extracted from the holes is referred to as extractability.

3.2 Prediction of Possible Contact-States

The extractable dual pegs, as shown in Fig. 2, have maximum lateral movements and to create different contact configurations, the pegs are rotated in clockwise and counterclockwise directions while maintaining contact. Based on the rotational direction of the pegs and typical mating geometries, the dual peg-hole disassembly process can result in 26 potential contact states, as presented in Fig. 3 [10]. These states can be classified into four groups, as shown in Fig. 4: (a) no contact, (b) one-point contact, (c) two-point contact, and (d) line contact. The optimal scenario would be to have no contact; however, this is rare and is not discussed in this paper. Typically, the process begins with two-point contact due to compliant manipulation and the presence of lateral and angular errors, as shown in Fig. 4c.

As the peg is extracted and the process may transition to one-point contact (Fig. 4b) or line contact (Fig. 4d) due to factors such as compliance, the position of the compliance centre, and initial positioning deviations. To progress from two-point to one-point contact, the peg must rotate during the extraction process, as shown in Fig. 4b. The single point contact state will persist until the peg is fully extracted from the hole.

Yanqiong and Xifang [11] have found that three-point and four-point contact states can happen in peg-in-hole insertion under specific conditions.

A three-point contact can only happen if Eqs. (4) and (5) are both satisfied, where θ represents the tilt angle of the peg, as shown in Fig. 5.

$$h \sin \theta + 2r_{P_1} \cos \theta = 2R_{H_1} \quad (4)$$

and,

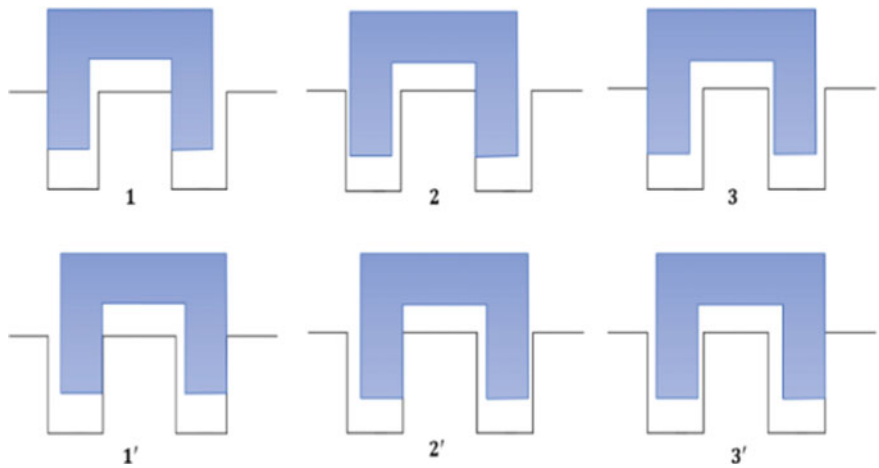


Fig. 2 Types of line contacts

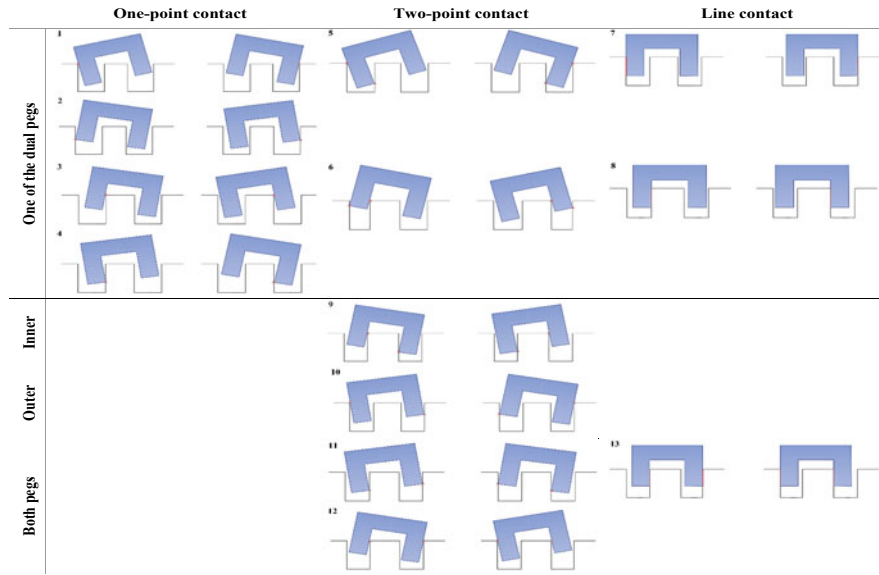


Fig. 3 Various contact states for dual-peg extractions

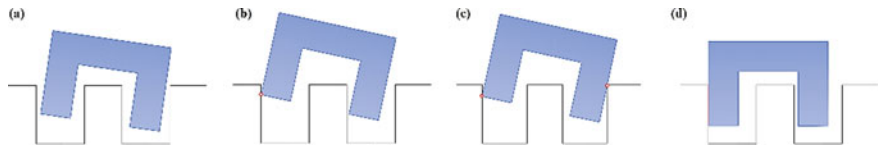


Fig. 4 Typical states of dual peg-hole disassembly process: **a** no contact, **b** one-point contact, **c** two-point contact, and **d** line contact

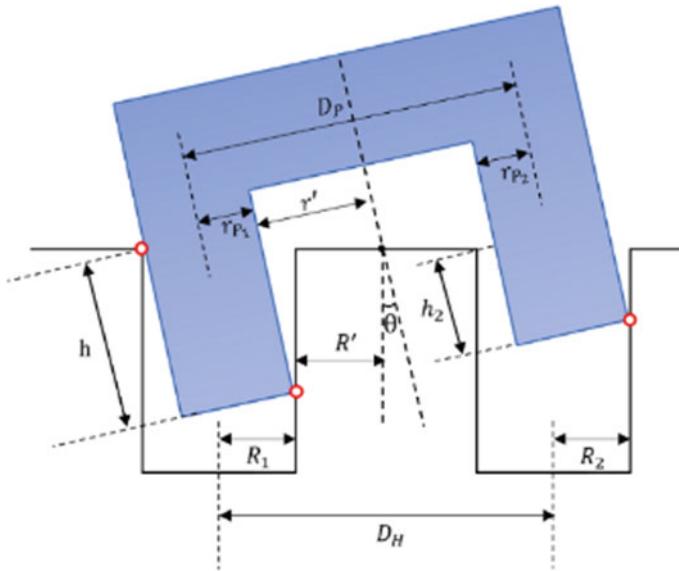


Fig. 5 Three-point contact state of dual peg-in-hole

$$h \sin \theta + (2r_{P_1} + 2r_{P_3} + 2r_{P_2}) \cos \theta = 2R_{H_1} + 2R_{H'} + 2R_{H_2} \quad (5)$$

Similarly, four-point contact can only happen if Eqs. (4), (6) are both satisfied (Fig. 5).

$$h_2 \sin \theta + (2r_{P_2}) \cos \theta = 2R_{H_2} \quad (6)$$

Therefore, three-point and four-point contacts are considered transitory and insignificant as they only happen at specific insertion depth points rather than a depth region. Hence, the focus of this study is on one-point and two-point contact states.

Jamming and wedging are common problems in peg-hole disassembly. Jamming occurs when forces and moments are improperly applied to pegs, causing an unmovable state for a peg. Wedging occurs during which, despite significant force insertion, pegs are locked in place.

During the process of peg-hole disassembly, the occurrence of jamming and wedging is common, particularly during the two-point contact state. To prevent jamming and wedging, it is necessary to decrease the size of the two-point contact region and control the location at which two-point contact occurs [12].

4 Force Analysis of Dual-Peg Extraction

To accurately model the extraction of dual pegs, it is essential to analyse the forces and moments involved in the process. Meeting a set of requirements is necessary for a successful extraction, as the dual pegs may encounter several states of contact, with some being preferable to others. To maintain the preferable states of contact, it is necessary to determine the conditions of the applied forces and moments.

As previously discussed, a dual-peg problem in two dimensions can have 26 potential states, as in Fig. 3. As we explained in Section III.B, three-point and four-point contacts are transitory and insignificant and thus are not discussed in this paper. The dual peg-hole problem is therefore similar to a single peg-hole regarding two-point contact states (Fig. 6).

The two-point contact states in the dual peg-hole can be classified into three groups (Fig. 6): (a) contact in one of the dual peg-holes, (b) external surfaces of the pegs in contact with the surfaces of the holes, and (c) internal surfaces of the pegs in contact with the surfaces of the holes. This section will analyse a contact from each of these categories.

4.1 Derivation of Force-Moment Conditions for Maintaining Contact-States

In this analysis, it is assumed that both pegs have uniform length. We consider the dimensions of the dual pegs and their configuration, as shown in Fig. 7. The reference frame for the dual pegs is located at the tip of the selected peg (Shown in orange), and all forces and torques acting on them are defined with respect to this frame.

Initially, the dual-pegs and the aperture are in a state of bi-point contact, and the angular deviation is minimal for ease of computation. This approximation is considered valid because in real-world scenarios, the angular discrepancy of the pegs is a few degrees at most. As shown in Fig. 8, δ_0 and β_0 denote the initial lateral

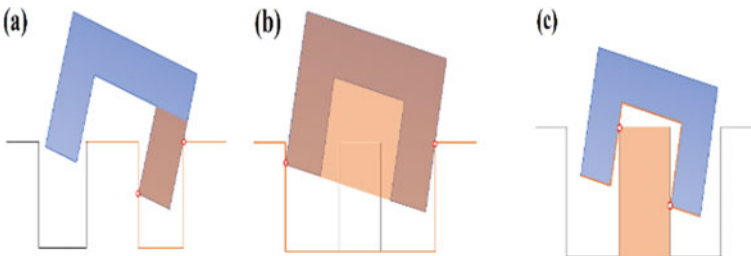


Fig. 6 Classification of two-point contact states in the dual peg-hole; **a** Contact between one of the dual-peg and hole, **b** External surfaces of pegs contact holes surfaces, and **c** Inner surfaces of pegs contact holes surfaces

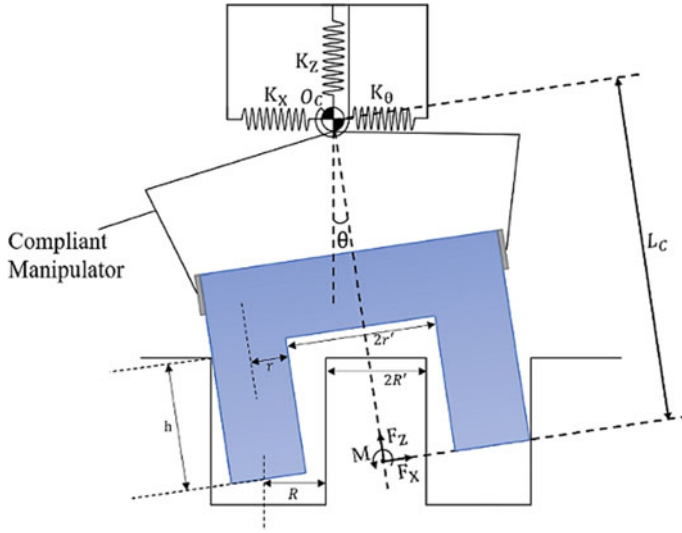


Fig. 7 Dimensions and reference frame for dual peg-hole

and angular deviations, respectively. The centre of compliance and the end of the peg are situated at U_0 and ε_0 distances, respectively, from the axis of the aperture.

Contact in One of the Dual Peg-Holes:

As illustrated in Fig. 6a, there are four potential contact states in this scenario and we will focus on one of these contact states to conduct a force analysis. Specifically, we will analyse quasi-static equilibrium of the dual pegs in Contact Mode 5 (Fig. 3), as illustrated in Fig. 9. Extraction forces (F_z), F_x , and torques (M) are imposed on the pegs at point O , which is the reference frame's origin. Throughout the disassembly process, the distances U and ε will undergo continuous change.

The path of the compliance *centre* can be deduced as:

$$\begin{cases} U + \varepsilon = L_C \sin \theta, & U - U_0 + (\varepsilon - \varepsilon_0) = L_C(\theta - \theta_0) \\ \varepsilon = r' \cos \theta - R' \\ U - U_0 = L_C(\theta - \theta_0) \end{cases} \quad (7)$$

In this equation, L_C is the distance between compliance centre and the aim peg tip, and h is the depth of peg extraction. During two-point contact, geometrical relations are as follows, based on the geometrical constraints:

$$R = \frac{h \sin \theta}{2} + r \cos \theta; \text{ if } \theta \approx 0 \text{ then } h\theta = 2CR, \\ C = \frac{R - r}{R}; C : \text{Clearance ratio} \quad (8)$$

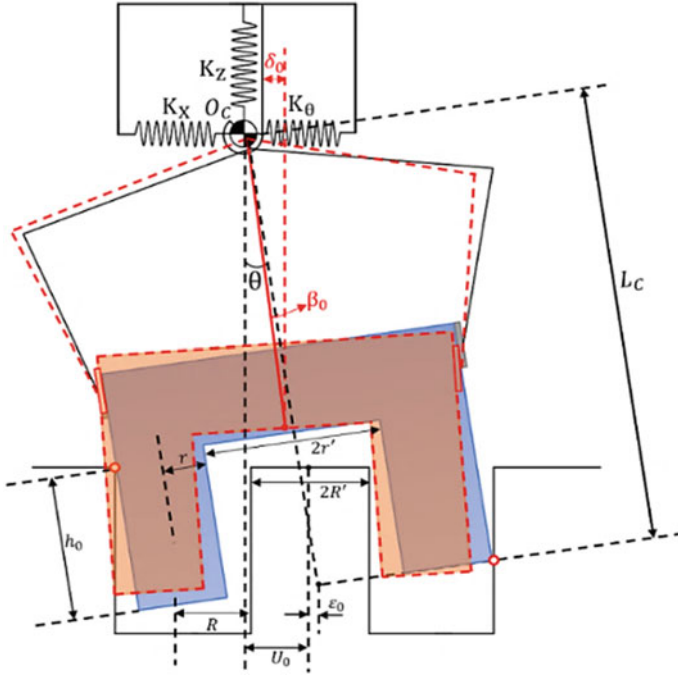


Fig. 8 Definition of initial position in dual peg-hole

Whitney's [8] method can be utilised to re-express contact and supporting forces at and around compliance centre in the coordinate frame fixed at the tip of the aim peg.

$$\begin{cases} F_x = F_{N2} - F_{N1}, & F_z = \mu(F_{N1} + F_{N2}) \\ M = (h - \mu r)F_{N1} + \mu r F_{N2} \end{cases} \quad (9)$$

The following is the applied force and moment by compliance centre:

$$\begin{cases} F_X = -K_X(\delta_0 + U_0 - U) \\ M = K_X L_C(\delta_0 + U_0 - U) + K_\theta(\beta_0 + \theta - \theta_0) \end{cases} \quad (10)$$

By assuming $F_{N2} = 0$ at point 2, it is possible to calculate the boundary conditions of the two-point contact. Accordingly, the contact forces are as follows:

$$\begin{cases} F_x = -F_{N1}, & F_z = \mu F_{N1} \\ M = (h - \mu r)F_{N1} \end{cases} \quad (11)$$

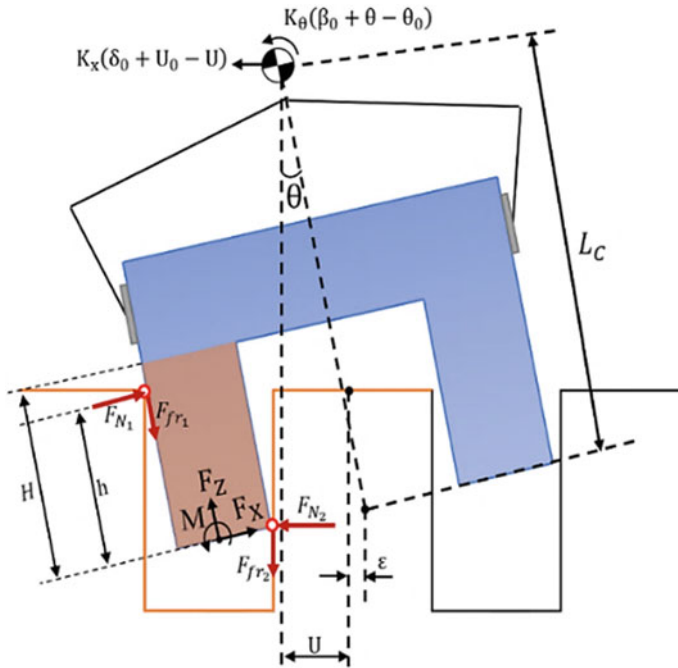


Fig. 9 Geometry and forces during the two-point contact in one of the dual peg-holes

The path of the centre of compliance in the boundary conditions of two-point contact state is expressed using Eqs. (7) and (12).

$$\begin{cases} \theta = \theta_0 - \beta_0 + \frac{K_x(h - \mu r - L_C)(L_C\beta_0 + \delta_0)}{K_x L_C(h - \mu r) - K_x L_C^2 + K_\theta} \\ U = U_0 + \delta_0 - \frac{K_\theta(L_C\beta_0 + \delta_0)}{K_x L_C(h - \mu r) - K_x L_C^2 + K_\theta} \end{cases} \quad (12)$$

By substituting Eq. (8) into Eq. (12), a quadratic equation can be generated, can be used to calculate extraction depth h :

$$\alpha h^2 + \beta h + \gamma = 0 \quad (13)$$

where,

$$\alpha = A + K_x L_C B$$

$$\beta = (E - \mu r K_x L_C) B - (L_C + \mu r) A - 2cR K_x L_C$$

$$\gamma = 2cR(\mu r K_x L_C - E), A = K_x(L_C\beta_0 + \delta_0)$$

$$B = \theta_0 - \beta_0 E = K_\theta - K_x L_C^2$$

The roots (extraction depth) of the Eq. (13) are:

$$h_2 = \frac{-\beta + \sqrt{\beta^2 - 4\alpha\gamma}}{2\alpha}, h_2' = \frac{-\beta - \sqrt{\beta^2 - 4\alpha\gamma}}{2\alpha} \quad (14)$$

The roots h_2 and h_2' represent the beginning and end of a two-point contact region can be found by solving Eq. (13). In one-point contact state, the geometrical parameters are as follows ($\theta \approx 0$):

$$\begin{cases} U = L_C \theta - \varepsilon, \varepsilon = r' \cos \theta - R' \\ U = L_C \theta - r' + R' \end{cases} \quad (15)$$

The equations for U and θ and of the one-point contact can be obtained by combining Eqs. (10) and (11) in a coordinate frame fixed to the selected peg tip.

$$\begin{cases} U = \delta_0 + U_0 - \frac{N_2 + K_\theta \theta}{K_x(h - \mu r - L_C)} \\ \theta = \frac{N_2 - K_x N_1(h - \mu r - L_C)}{-K_x L_C(h - \mu r - L_C) - K_\theta} \end{cases} \quad (16)$$

where:

$$N_1 = \delta_0 + U_0 - R' + r', \quad N_2 = K_\theta(\beta_0 - \theta_0) \quad (17)$$

The reaction force and extraction force during the two-point contact can be obtained using Eq. (9), which is composed of three equations and three unknown parameters:

$$\begin{cases} F_{N1} = -\frac{\mu r}{h} F_x + \frac{1}{h} M, \quad F_{N2} = \frac{h - \mu r}{h} F_x + \frac{1}{h} M \\ F_z = \frac{M}{\lambda r} - \frac{\mu}{\lambda} (1 - \lambda) F_x; \quad \lambda = \frac{h}{2r\mu} \end{cases} \quad (18)$$

Solving Eq. (10) with Eqs. (7) and (8) leads to F_x and M for the two-point contact state.

$$\begin{cases} F_x = -k_x(\delta_0 + L_C \theta_0 - \frac{c D L_C}{h}) \\ M = k_x L_C(\delta_0 + L_C \theta_0) - \frac{k_x L_C^2 C D}{h} + k_\theta(\beta_0 - \theta_0) + \frac{k_\theta C D}{h} \end{cases} \quad (19)$$

By substituting the Eq. (16) into Eq. (11), the extraction force in the one-point contact state is calculated.

$$F_z = \frac{\mu k_\theta(\theta - \theta_0 + \beta_0)}{(h - \mu r - L_C)} \quad (20)$$

External Surfaces of Pegs Contact Holes Surfaces:

This part examines the two-point contact state in which external surfaces of pegs contact hole surfaces. As illustrated in Fig. 6b, this state is treated as one peg-hole. There are four potential contact states in this scenario, and we will focus on one of these contact states to conduct a force analysis. The quasi-static equilibrium of the dual pegs in the contact Mode 10 (Fig. 3) is analysed. Extraction forces (F_X and F_Z) and torques (M) are imposed on the pegs at point O, the reference frame's origin. The distances U and ε (Fig. 10) undergo continuous variation during the disassembly process.

The trajectory of the compliance centre in a two-point contact state under boundary conditions can be described as following:

$$\begin{cases} \theta = \theta_0 - \beta_0 + \frac{K_x(h-\mu r-L_C)(L_C\beta_0+\delta_0+CR-\varepsilon_0)}{K_x L_C(h-\mu r)-K_x L_C^2+K_\theta} \\ U = U_0 + \delta_0 - \frac{K_\theta(L_C\beta_0+\delta_0+CR-\varepsilon_0)}{K_x L_C(h-\mu r)-K_x L_C^2+K_\theta} \end{cases} \quad (21)$$

The path of the compliance centre during one-point contact:

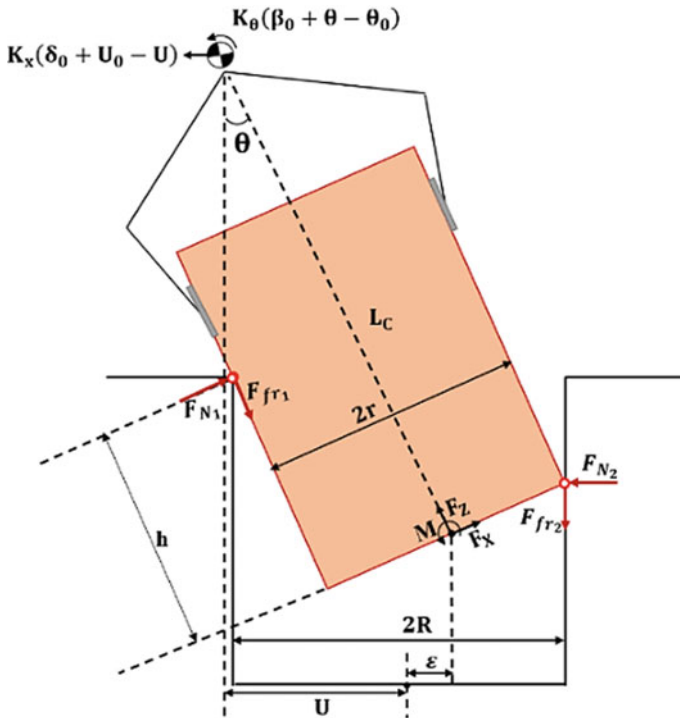


Fig. 10 Geometry and forces during the two-point contact in the external surfaces of pegs contact holes surfaces

$$\begin{cases} U = \delta_0 + U_0 - \frac{N_2 + K_\theta \theta}{K_x(h - \mu r - L_C)} \\ \theta = \frac{N_2 - K_x N_1(h - \mu r - L_C)}{-K_x(L_C - h)(h - \mu r - L_C) - K_\theta} \end{cases} \quad (22)$$

where;

$$N_1 = \delta_0 + U_0 - CR, \quad N_2 = K_\theta(\beta_0 - \theta_0) \quad (23)$$

F_X and M for two-point contact:

$$\begin{cases} F_x = -k_x(\delta_0 - \varepsilon_0 + L_C\theta_0 + CD/2 - \frac{cDL_C}{h}) \\ M = k_x L_C(\delta_0 - \varepsilon_0 + L_C\theta_0 + CD/2) - \frac{k_x L_C^2 CD}{h} + k_\theta(\beta_0 - \theta_0) + \frac{k_\theta CD}{h} \end{cases} \quad (24)$$

The extraction force in the one-point contact state is therefore:

$$F_z = \frac{\mu k_\theta(\theta - \theta_0 + \beta_0)}{(h - \mu r - L_C)} \quad (25)$$

Inner Surfaces of Pegs Contact Holes Surfaces:

In this section, a contact state where the internal surfaces of the pegs and the holes are in two-point contact are analysed. As depicted in Fig. 6c, this state is depicted as an inverted peg-hole. There are two possible contact states in this scenario.

Similar to the previous sections, we will present an example of force analysis for one of these contact states. The quasi-static equilibrium condition of the double pegs in contact mode 9, as listed in Fig. 3, will be considered. The distances U and ε (Fig. 11) change continuously during the disassembly process.

The path of the compliance centre in the boundary conditions of two-point contact state is expressed as follows:

$$\begin{cases} \theta = \theta_0 - \beta_0 + \frac{K_x(-\mu R' - L_C)(\delta_0 + L_C\beta_0)}{K_x L_C(h - \mu R') - K_x L_C^2 + K_\theta} \\ U = U_0 + \beta_0 + \frac{K_\theta(L_C\beta_0 + \delta_0)}{K_x L_C(h - \mu R') - K_x L_C^2 + K_\theta} \end{cases} \quad (26)$$

The path of the compliance centre during one-point contact, θ and U , as in the previous sections, is obtained as follows:

$$\begin{cases} U = \delta_0 + U_0 - \frac{N_2 + K_\theta \theta}{K_x(h - \mu R' - L_C)} \\ \theta = \frac{N_2 - K_x N_1(h - \mu R' - L_C)}{-K_x L_C(h - \mu R' - L_C) - K_\theta} \end{cases} \quad (27)$$

where

$$N_1 = \delta_0 + U_0 - R' + r', \quad N_2 = K_\theta(\beta_0 - \theta_0) \quad (28)$$

F_X and M for two-point contact:

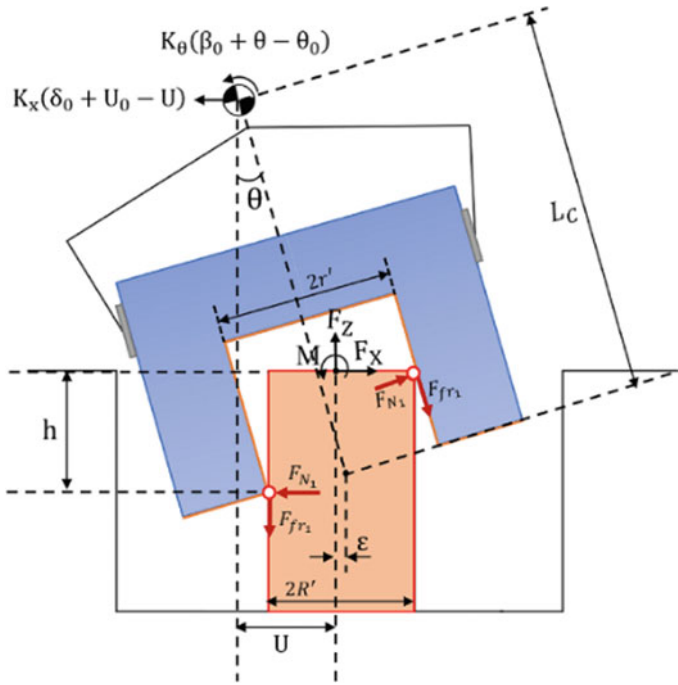


Fig. 11 Geometry and forces during the two-point contact in the inner surfaces of pegs contact holes surfaces

$$\begin{cases} F_x = -k_x \left(\delta_0 + L_C \theta_0 - \frac{L_C (-2R'C)}{h} \right) \\ M = k_x L_C (\delta_0 + L_C \theta_0 - h \theta - 2R'C) - \frac{k_x L_C^2 (-2R'C)}{h} - k_x h \delta_0 \\ \quad + k_\theta (\beta_0 - \theta_0) + \frac{k_\theta (-2R'C)}{h} \end{cases} \quad (29)$$

The extraction force in the one-point contact state is calculated:

$$F_z = \frac{-\mu k_\theta (\theta - \theta_0 + \beta_0)}{(h - \mu R' - L_C)} \quad (30)$$

Region of Extraction Depth:

In this article, Eq. (13) represents the depth of extraction, h , through the parameters h_2 and h'_2 , which are the two roots. The values of h_2 and h'_2 in the calculation results indicate the start and end of the two-point contact state, respectively.

If h'_2 is less than h_0 , it implies that the peg-hole system is in a two-point contact state at the beginning of disassembly. When h_0 is smaller than h'_2 and h'_2 is less than h_2 , the peg-hole system would initially be in a one-point contact state, and at least one transformation occurs between the one-point and two-point contact states during disassembly. If the equations have no solution, then two-point contact cannot occur.

If h_0 is less than h'_2 and h'_2 is equal to h_2 , then the peg-hole system is in a two-point contact state at least for a moment during the disassembly process. The position and height of a two-point contact region are influenced by various factors, such as the geometrical parameters of the hole-peg system, the location of the compliance centre, initial position errors, and degree of compliance.

Jamming Region:

Jamming can be determined using equilibrium equations for rigid pegs [3]. Combining Eq. (9) reveal the linear relationship for a peg in two-point contact:

$$\frac{M}{hF_Z} = \frac{h}{2r\mu} - \frac{F_X}{F_Z} \left(\frac{h}{2r} - \mu \right) \quad (31)$$

$$\frac{F_X}{F_Z} = \pm \frac{1}{\mu} \quad (32)$$

Based on (31) and (32);

$$\frac{M}{hF_Z} = \pm \left(\frac{h}{2r\mu} + 1 \right) \quad (33)$$

In Fig. 12, the equilibrium instance during peg extraction from the hole is defined by Eqs. (31) and (32), which form the outline of a parallelogram. This instance is determined by the combination of F_X , F_Z , and M .

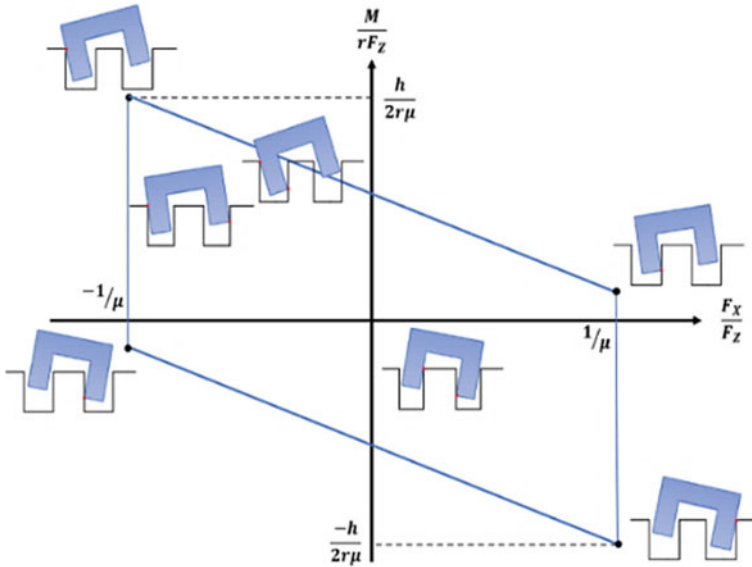


Fig. 12 Jamming diagrams for the dual-peg extraction problem based on contact forces [10]

disassembly problems. Compliant manipulators were used to derive geometric and force/moment conditions for each contact state, Compliant manipulators were used to derive geometric and force/moment conditions for each contact state, demonstrating significant potential for developing more accurate and reliable robotic systems for disassembly and remanufacturing applications. The study also found that a dual peg-hole during the extraction process has very similar features to one peg-hole, which means the techniques for one peg-hole such as compliance centre can potentially be adopted for dual peg-hole, and the same strategy can potentially help. In future work, experiments will be done for validation. This study provides a foundation for future research in this area and highlights the importance of a systematic approach to address the challenges of dual-peg hole extraction.

Appendix

Variable	Description
C	Clearance ratio
D	Diameter of the hole (mm)
F_x	Lateral force (N)
F_{fr1}, F_{fr2}	Friction force at contact point 1 & 2 (N)
F_{N1}, F_{N2}	Reaction force at contact point 1 & 2 (N)
F_z	Extraction force (N)
h	Extraction depth (mm)
h_0	Initial depth of the peg in the hole (mm)
H	Height of each peg (mm)
K_x	Lateral stiffness of the compliant manipulator ($N\ mm^{-1}$)
K_z	Vertical stiffness of the compliant manipulator ($N\ mm^{-1}$)
K_θ	Rotational stiffness of the compliant manipulator ($N.mm\ rad^{-1}$)
L_C	Location of the compliance centre (mm)
M	Moment applied on the peg (Nmm)
r	Radius of each peg (mm)
R	Radius of each hole (mm)
U_0	Initial distance between the compliance centre and the hole axis (mm)
U	Distance between the compliance centre and the hole axis (mm)
β_0	Initial angular error (rad)
δ_0	Initial lateral error (mm)
ε	Distance between the peg tip and the hole axis (mm)
ε_0	Initial distance between the peg tip and the hole axis (mm)
θ	Tilt angle of the peg (rad)

(continued)

(continued)

Variable	Description
θ_0	Initial tilt angle of the peg (rad)
μ	Coefficient of friction

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Disassembly Strategies for Remanufacturing: Experiences from a Learning Factory



Jenny Coenen, Hugo Makkink, and Mirjam Zijderveld

Abstract This paper describes some explorations on the concept of disassemblability as an important circularity indicator for products because of its severe impact on reuse value. Although usefulness of the concept for determining disassembly strategies and for improving circular product design clearly shows in earlier studies, the link with Industry 4.0 (I4.0)-related process innovation is still underexposed. For further technical development of the field of remanufacturing, research is needed on tools & training for operators, diagnostics, disassembly/repair instructions and forms of operator support. This includes the use of IoT and cobots in remanufacturing lines for automatic disassembly, sorting and recognition methods; providing guidance for operators and reduction of change-over times. A prototype for a disassembly work cell for a mobile phone has been developed together with researchers and students. This includes the removal of screws by means of a cobot using both vision & the available info in the product's Bill-Of-Materials, the removal of covers, opening of snap fits and replacement of modules. This prototyping demonstrates that it is relatively easy to automate disassembly operations for an undamaged product, that has been designed with reparability in mind and for which product data and models are available. Process innovations like robotisation influence the disassemblability in a positive way, but current indicators like a Disassembly Index (DI) can't reflect this properly. This study therefore concludes with suggestions for an evaluation of disassemblability by looking at the interaction between product, process and resources in a coherent way.

J. Coenen (✉) · H. Makkink · M. Zijderveld
The Hague University of Applied Sciences, Hague, The Netherlands
e-mail: j.m.g.coenen@hhs.nl

H. Makkink
e-mail: h.m.makkink@hhs.nl

M. Zijderveld
e-mail: m.j.w.zijderveld@hhs.nl

1 Knowledge Gap Automatic Disassembly

An important aspect of the circular economy is closing product loops by means of circular manufacturing. Whatever level of value retention is aimed for and whether this implies Reuse, Remanufacturing, Refurbish, Repair or Recycling: technically feasible and cost-efficient disassembly processes are required. Scalable, rationalized disassembly processes are yet to be developed, as Jungbluth [1] explains disassembly is mainly manual work. This is considered problematic as this high fraction of manual labour makes disassembly expensive. Additionally, disassembly work is potentially heavy and unsafe. This has a negative impact on the further spread of circular manufacturing. Whilst principles of Industry 4.0 gradually find their way to manufacturing and bring advantages of flexibility, connectivity, traceability, human–robot collaboration, product-service orientation and interoperability, such progress is hardly made in remanufacturing. In both [2] and [3] a gap is identified in how CE and Industry 4.0 principles are practiced in manufacturing companies or impact CE business models. Research on the profitability and feasibility of disassembly systems so far concentrates on manual disassembly [4]. Only little research evaluates robotic disassembly, and this is usually aimed at robotic disassembly for recycling posing different requirements than robotic disassembly for remanufacturing. In [5] an inventory of emerging I4.0 tech for remanufacturing is provided and reported that few examples for robotic disassembly can be found. Also in [5] it is concluded that robots could play a role in disassembly and recovery based on desk research but also on a large survey of project managers, a multiple case study of 27 projects, and 31 personal interviews that mainly confirms the literature review developed by Rosa et al. [2]. In short, a knowledge gap on automatic disassembly is identified that leads to missed opportunities for making disassembly processes more successful.

2 Research Questions and Methods for This Paper

In [6] I4.0 innovations required for scaling remanufacturing are described. These focus on: -Improving disassembly and remanufacturing process execution at the level of a work cell, mainly by better tooling and methods; -Improvement of operations at the remanufacturing line (better layout, line balancing, planning and control of process) and Improving information collection and decision support for both levels. This paper refines the aspects of robotic disassembly at work cell level and the **objective** is to **understand and improve the ‘disassemblability’ of products by automation**. This leads to the following research questions: -How Disassemblability can be used to determine a feasible disassembly strategy; -In what aspects does this differ between manual and robotic disassembly; -How could a knowledge base of disassembly rules and KPIs for disassembly be used and maintained in future such that it reflects and encourages further innovation? To achieve this, different methods from academic literature for assessing disassemblability and determining

disassembly strategy will be compared. The principle of expressing disassemblability is then shown for an example product. The object for this experiment is carefully picked: a phone for which the aspects of disassemblability have been well-considered by design. This increases the likelihood of success for the subsequent attempt at automatic disassembly. (Which is considered important for a first prototype in a setting for learning and education). This next step of building a prototype for disassembly of the phone is executed by students of the “RE/manufacturing Lab” of The Hague University of Applied Sciences. Subsequently evaluation of the predicted and experienced disassemblability and success of the strategy is carried out. Finally, some exploration on a possible learning model for ‘disassemblability’ will be provisionally illustrated by means of the results of the presented experiment. So, the **contribution of this paper** is a hands-on demonstrator of a disassembly cell and additionally the presentation of a method on how to systematically learn and improve from tested disassembly strategies by including this in an improved concept of disassemblability.

3 Assessment of Disassemblability

Disassemblability assessment is important for: improving designs, determining technical (and economical) feasibility of disassembly, deciding on disassembly strategy and improving disassembly processes. Disassemblability Indicators are expected to play a role in demonstration of circularity for instance in the context of legislation like Eco-design for Sustainable Products Regulation, Right-to-Repair and the Critical Raw Materials Act [7]. It expresses the required effort for disassembly of an object and the likelihood that the disassembly will succeed without permanent damage to the object. The principle of a Disassembly Index (DI) is explained in i.e. [8–10] and primarily based on complexity and accessibility scores for individual connectors and joints cumulating in an overall score based on the product breakdown structure. Complexity is considered to be the result of tools needed; amount, type and accessibility of connectors, difficulty of handling products and components (because of weight, size, thickness, stability, visibility etc.). A DI can be used to estimate required disassembly effort and duration by relating the index to a reference value for a known component. A more procedural approach is to determine first the disassembly path and estimate disassembly time from this analysis. Chang [11] gives an overview of methods for disassembly planning. To find all feasible sequences graph-based methods; geometry-based methods (based on topology graph wave propagation) and CAD-based methods (based on precedence matrix derived from CAD model) can be applied. Other disassembly planning methods additionally add uncertainties of product conditions to the sequence planning during operation. Illustrations of such methods can be found in [8]. The identified feasible sequences can be optimized by means of formal optimization algorithms or intelligent methods, or otherwise the shortest path is usually preferred. To estimate disassembly time the eDIM-metric can be used [12]. With the components and disassembly sequence provided, the basic disassembly task durations can be looked up from a database filled with indications

of the time based on MOST (this is a Work Measurement System and its use in disassembly is for instance explained in [13]. De Fazio [14] describes similar parameters for ease of disassembly but adds the aspect of fastener reusability/reversibility. The joining methods (welding, gluing, sewing, bolting, screwing, clicking etc.) and use of fasteners (nuts and bolts, rivets, screws, snap-fits) have a large impact on the resulting disassemblability. Marconi [15] adds corrective factors for the effective disassembly time that consider the actual conditions of a product and its components (e.g., deformation, rust and wear). Finally, the availability of documentation and labelling including assembly instructions and labelling of components, in order to disassemble a product correctly and safely is a factor.

4 Disassemblability of Phone

In this study, to determine the disassembly index at component level, a modified version of the method found in [10] is used that includes the type of connections between components, the condition of the components, the accessibility depth of the connections and a penalty for damage that is done to other components. *Type Connector (TC)* scores range from 0.1 for difficult connectors like welds or hard glues, to 1 for easy clicks, snapfits or magnets. *Penalty* scores (*cp*) indicate if the connector score is: intact [1] or damaged [0.2] or dirty [0.4]. *Accessibility (A)* scores depend on *disassembly depth (d)* that illustrates how many parts to remove before access is gained and degree of damage done to other parts (*ap*). *Damage penalties (ap)* range from 0.8 (Full repair possible) to 0.1 (irreversibly damaged). This gives a *Disassembly Index* per connection (DI_c). To get an impression of the overall DI at product level, the average could be used. This leads to the following equations for Accessibility and Disassembly Index.

$$A = ap * (1 - (d / 10)) \quad (1)$$

for $0 < d \leq 10$

$$DI_c = 2 / ((1 / cp * TC) + (1 / A)) \quad (2)$$

In Fig. 1 the example product for this study and its required disassembly steps are illustrated. Then Table 1 shows the DI scores per connection. As expected, the DI is very high (close to 1) by design and the disassembly sequence is straightforward. It should be noted that Eqs. (1) and (2) and the used tuning parameters present a much simplified view on ‘Disassemblability’ that is not sufficiently accurate to predict disassembly effort or duration; but merely serves to rank disassembly tasks in terms of expected effort.

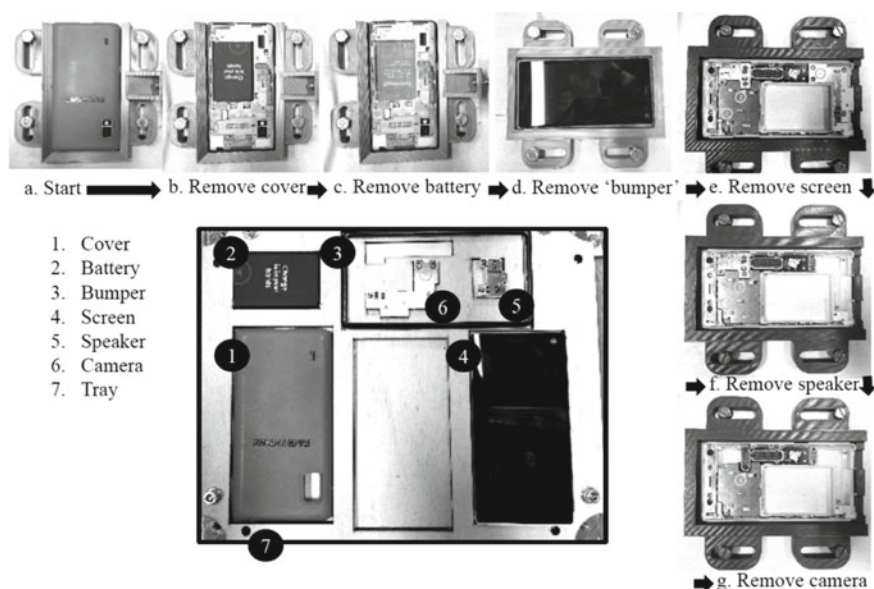


Fig. 1 Disassembly sequence for test product

5 Autonomous Disassembly

Three student teams have been appointed the task of demonstrating a feasible automatic disassembly strategy for the test product. The first team should demonstrate the feasibility of removing screws automatically, the second team should remove the cover, battery and bumper while the last assignment consisted of integrating the previous strategies and subsequently removing the speaker and camera module. A starting point for development of the robotic disassembly cell was to use a 6-axis cobot (Doosan A0509s). This cobot type was selected earlier for its flexibility in lab work aimed at manufacturing and is used for several projects at the university.

Table 2 shows the required functions for the 6 identified disassembly steps in Fig. 1. For identifying the product using a RFID tag was chosen. This is in line with the concept of the 'Learning Factory' that is developed within the "RE/manufacturing Lab" in which incoming products are put on tagged trays and the object is immediately labelled with a unique ID that is linked with a tray position. All move and positioning functions can be executed by means of the cobot. To fixate the phone for the removal of the cover a pneumatic actuator was developed (Fig. 2). In an earlier version this was fulfilled by an electric actuator, but as will be explained this station also uses compressed air for the vacuum tools for lifting, so this was a more convenient solution. To switch between the different tools an external tool exchange mechanism was developed, see Fig. 4. Tool heads easily click on the cobot arm by moving a half turn. Tool heads can be removed from the cobot by positioning them in the exchange station and then moving a half turn in reversed direction. Tools have a fixed position in

Table 1 DI for example product phone

	Type connector (TC)	Score TC	Connector penalty (cp)	Disassembly path	Depth (d)	Damage penalty (ap)	Accessibility (A)	Disassembly index (DI _c)
Cover	Click	1	1	Freely	0	1	1	1
Battery	Click	1	1	Remove cover (no damage)	1	1	0.9	0.95
Bumper	Click	1	1	Freely	0	1	1	1
Screen	Click	1	1	Remove bumper (no damage)	1	1	0.9	0.95
Speaker	Screw	0.8	1	Remove screen (no damage)	2	1	0.8	0.8
Camera	Screw	0.8	1	Remove screen (no damage)	2	1	0.8	0.8

the exchange station throughout a disassembly routine. Several tools were manually tested for the 'pry loose' and 'lift' operations. A 'putty knife' like tool was developed to remove the cover (Fig. 4). A pneumatic suction cup tool was made for lifting. In order to have sufficient grasp for the larger components and to be sufficiently accurate to pick up smaller parts, two tool heads were needed: one with one cup and one with three cups (Fig. 2). Between the remove battery and remove bumper operation, the product should be turned over to gain access to the topside. A tilting skid (see Fig. 1) was devised for this handling: the cobot arm put the phone in the sloped skid, it will slip downwards towards a predictable position and then the cobot arm picks it up from the other side. A screwing tool driven by a DC motor (cheap solution that can deliver enough torque) was included by means of the same tool exchange principle. For locating and identifying the screws in the phone, the students opted for use of a HD camera (accessory to the cobot arm). Strictly speaking this shouldn't be necessary as both the phone properties, its orientation in the cell and the disassembly locations are known upon entry (because of fixed positions in the work cell for the operations). This can be seen in the left part of Fig. 2 that shows the layout of the cell and item 7 in Fig. 1 that shows the layout of the tray. Tests with unscrewing based on fixed position of the screw showed a lower success rate of the operation than with camera images (systematic tests to quantify the significance of this result haven't been executed yet). But the students rightfully reasoned that a follow-up development step for the disassembly station would be to work with other product types too and that a camera should be included anyhow. Therefore, they decided to opt for the higher accuracy of guiding the unscrewing operation by means of vision. For communication and control, the students decided to use the IOs of the cobot for controlling the pneumatic switches, communication with the camera and the power supply to the DC motor.

The robotic work cell as shown in Fig. 2 demonstrates that it is indeed possible to setup in relatively short time a disassembly robot for a product with a high DI. Some reflections on the realised result are: -The placement of the tools and dismantling aids is not optimal considering the required cobot arm movements. This could easily be improved by switching the knife tool with the screw tool. This would also require some changes in the operator-robot interface such that tool head locations can be assigned easily before starting a new routine, taking into account the required tool changes. -The tilting skid location might better have been switched with remove screen, such that less robot movement is required. This should be tested though as it introduces collision risk (Fig. 3).

This may have another advantage that has not been tested yet, but to prevent a time-consuming tool change it might be better to put the phone in the tilting skid before picking up and removing the bumper. The bumper will fall off, probably after the tilting action and could be swooped up after the phone has been positioned to the remove screen position. With the camera it should be possible to detect the location of the bumper. Another possible improvement that has not yet been tested is if time can be saved by directly sending the screw tool to the theoretical position of the screws and only using the vision function when the first screw attempt is unsuccessful. Also bringing already the next phone to the 'remove screen' position

Table 2 Options for disassembly functions

Main function	Function	Option 1	Option 2	Option 3
Scan (a)	Identify product	QR/Barcode	RFID	Recognition (with vision)
Move (a, d, e, e)	Move product to disassembly position	6-axis cobot arm		
Tool change & positioning (a)	Fixate product in disassembly position	Pneumatic actuator	Electric actuator	Vacuum
Tool change & positioning (b, b, d, e, f, g)	Return tool	6-axis cobot arm		
Tool change & positioning (b, b, d, e, f, g)	Change tools	Tool exchange mechanism on arm	Tool revolver	External tool mechanism
Tool change & positioning (b, b, c, d, f, g)	Move tool to disassembly position	6-axis cobot arm		
Disassembly (b)	Pry component loose	Putty knife	Crowbar	
Disassembly (b, c, d, e, f, g)	Lift component out	Vacuum	Magnets	Gripper
Move (b, c, d, e, f, g)	Move component to output tray	6-axis cobot arm		
Move (e)	Flip over product	Gravity-based tilt	Vacuum tool with turning skid	
Scan (f, g)	Identify screw type	HD camera	Lookup/known in BOM	
Scan (f, g)	Identify screw position	HD camera	Lookup/known relative distance to anchor point	Lookup/known fixed position in workstation
Disassembly (f, g)	Unscrew	DC motor	Servo motor	Step motor

when returning from the tool change station might save some time in a situation of subsequent repairs. With respect to possible improvements in the already very good design-for-disassembly, one suggestion was made by the students and that is to dull the reflection of the screw heads as that makes the camera recognition process quicker and more accurate. Another consideration is whether preventing a turn-the-product around (easy for human, difficult for robot) action by change of design is possible as this will also reduce robotic disassembly time significantly. Looking at the design of the work cell from the perspective of flexibility there are also some considerations. Within the current setup the cell cannot deal with comparable products that have slightly different dimensions. In order to realise this, the fixation ‘slots’ for the

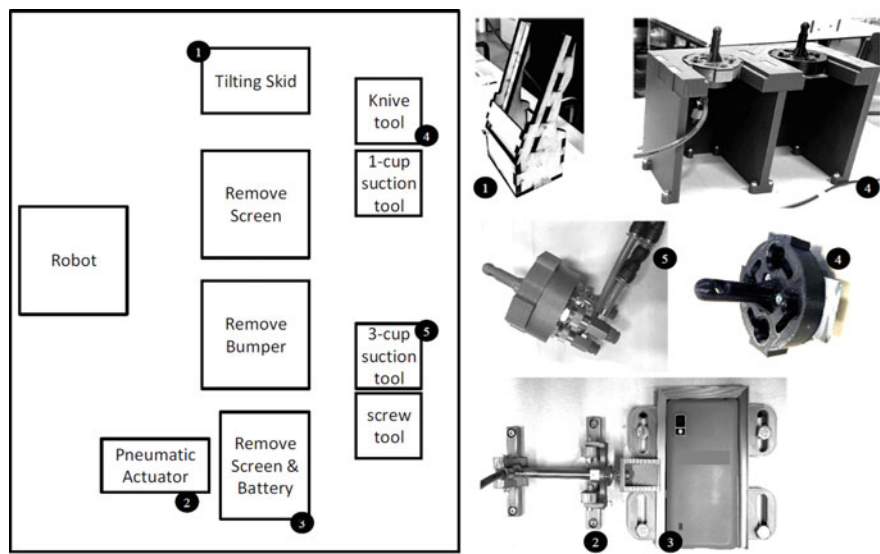
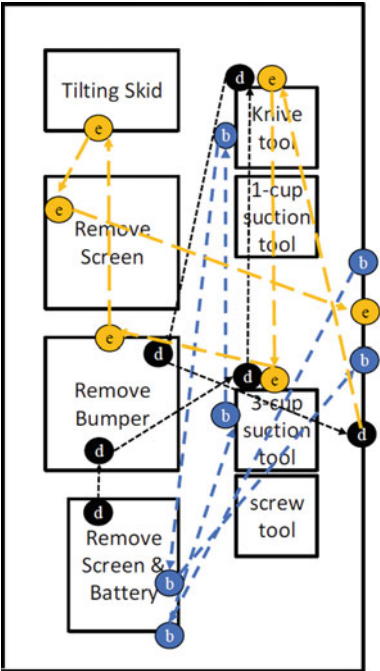


Fig. 2 Details of disassembly prototype

Fig. 3 Spaghetti diagram of the cobot arm movements



flexible removal actions should be made adjustable which might be realised with the same actuator mechanism as already built for the fixation for cover removal. The actual station can't deal with damaged or modified parts that ask for an alternative disassembly strategy. This has yet to be figured out and, at the very least, damaged or modified parts should be clearly separated from non-damaged original parts.

6 Disassemblability from Process and Resource Perspective

These results show that a disassemblability metric is useful to estimate the required effort for disassembly and reuse value of products. Such a metric should not solely be determined by product properties, but also properly reflect the interaction between product design, product state, process and resource capabilities. The described indicators from literature at best take the tools needed into account, but a systematic comparison of required versus available tools is not made yet. The described approach to use a database with reference values for manual disassembly handlings to estimate disassembly time should be expanded with lookup tables for automatic disassembly, that also take motion distances in the work cell into account. Further on, manipulation and identification or location tasks should be critically evaluated (as this small experiment already showed that flipping and low visibility of screws have relatively large impact on the efficiency of the process). No verified data are available yet to fill this database and such a set of rules and indicators for disassembly will be under continuous development: Circular design principles are applied more and more, leading at some point in time to products that are easier to disassemble. But also tools, resources and processes will be further innovated under the stimulating pressure of legislation on circularity, and hopefully also more successful business models for circular manufacturing. From the prototype in this study, it can be seen that principles of flexible manufacturing (both volume and mix flexibility) should be implemented to realise reduction of change-over time. This is particularly relevant considering developments in mass-customisation that implies dealing with many different product variants as well. Also, the execution of the disassemblability test itself should be enhanced. For instance by applying automatic disassembly evaluation in which the aspects of disassembly processes, resources (machines specifications, prior production data) and facilities (disassembly line capabilities) are also accounted for. This asks for a more holonic approach in which product, process and resource knowledge is combined and leads to different results for different combinations. Therefore a 'learning model' must be developed that over time will learn to deal with an increasing number of different scenarios, product designs, recovery processes, facilities etc. To achieve this predicted and realised disassembly KPIs should systematically be compared and updated as is shown in Fig. 4.

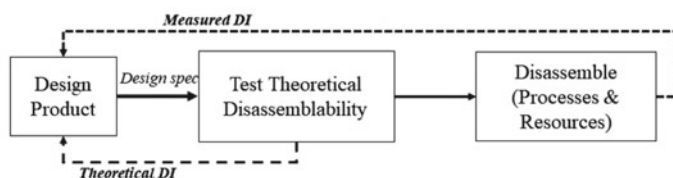
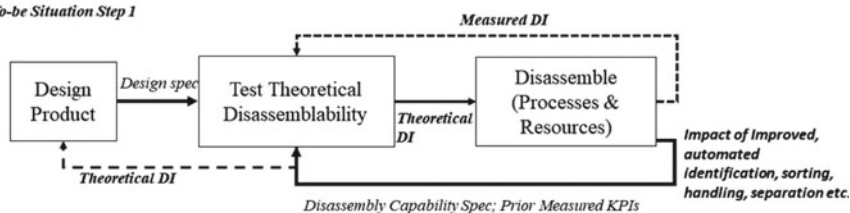
Current Situation*To-be Situation Step 1*

Fig. 4 Proposed learning model for disassembly KPIs

7 Conclusions and Future Work

Systematic evaluation of the disassembly index in the simplified form as presented in this paper provides a good starting point for the required functionality of an automatic disassembly process, especially when this is further implemented in a more advanced way (automatic analysis of the product model, including required tools, including required and available documentation). But to use it for automatic disassembly as well, the DI method should also include process and resource properties. As such, a more extensive disassembly path planning and resource allocation should be executed before the process is executed. In order to make this a viable approach for high variety product flows, further digitisation of the process is needed, like automatic interpretation of product information and implementation of principles of reconfigurable manufacturing. The project helped to understand and improve the disassemblability of products by means of automation, but also shows that there is still work to do in terms of scaling up to more flexible and agile disassembly processes that work for a variety of product types. The intended contribution of providing a successful example of a disassembly cell was achieved and a first outlook was given on how to systematically expand the knowledge base such that reuse value can be better predicted. Based on these results the “RE/manufacturing lab” of The Hague University of Applied Sciences has defined a further research agenda for the coming years in which the aspects of flexibility, collection of ‘product passport’ data and the future of the remanufacturing shop-floor from the operator’s perspective will be further investigated. Follow-up demonstrators of the disassembly station presented in this paper should be able to deal with different products and a more medium or lower disassemblability to demonstrate the scalability of automatic disassembly. This is not only relevant for companies struggling with similar questions, but also brings

the very important topic of circular manufacturing prominently into the education programme of future professionals.

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RE-AM Combined Use to Facilitate Decision-Making in Remanufacturing



Alessandro Greco , Pasquale Manco , America Califano ,
and Salvatore Gerbino 

Abstract In remanufacturing, Reverse Engineering (RE) tools and techniques could become essential in the rapid creation of digital 3D models of existing components, especially when drawings are no longer available. These models can be used to investigate potential remanufacturable parts, identify damages or defects and assist in the decision-making process for as-is rebuilding or redesigning of the part to improve performance. In this context, Additive Manufacturing (AM) technology is particularly well suited due to its capability to rapidly produce parts with minimal geometry constraints and at relatively low cost. This study proposes a methodological procedure based on the combined use of RE-AM to facilitate the remanufacturing decision-making process for better part performance and strategy. Moreover, through the use of Machine Learning (ML) algorithms, damages can be automatically and objectively identified and quantified. An application case is used to demonstrate the effectiveness of the proposed approach.

Keywords Remanufacturing · Reverse engineering · Additive manufacturing · Methodological procedure · Machine learning

1 Introduction

In recent years, there has been a growing interest in sustainable manufacturing practices and the reduction of environmental impact. As a result, many manufacturing companies are introducing remanufacturing as a viable solution to extend the

A. Greco · P. Manco (✉) · S. Gerbino
Department of Engineering, University of Campania Luigi Vanvitelli, Via Roma 29, 81031 Aversa (CE), Italy
e-mail: pasquale.manco@unicampania.it

A. Califano
Department of Industrial Engineering, University of Salerno, Via G. Paolo II 132, 84084 Fisciano (SA), Italy

lifecycle of products and reduce waste. Indeed, several engineering parts, industrial and commonly used machines, tools, machinery parts, and so on, are periodically subjected to hard operating conditions. These may concern overloads, impacts, fatigue, vibrations, high thermal cycles, erosions, etc. [1]. The loss of functionality, as well as failures of parts, often involves the replacement of components or even the entire machine, generating a massive amount of material waste. To limit this phenomenon, remanufacturing (RMfg) involves the process of restoring used products to their original working condition, often overcoming their original performance specifications [2].

This practice requires critical decisions, made at various stages of the process. Decision making in remanufacturing involves complex considerations for determining whether a product is suitable for remanufacturing, assessing the feasibility and cost-effectiveness of remanufacturing compared to alternative options, selecting the appropriate techniques, and integrating the suitable tools. The integration of these considerations is essential to optimize the remanufacturing process and achieve sustainable outcomes.

To enhance the effectiveness of remanufacturing, the literature proposes various methodological frameworks, often incorporating the integration of technologies, as potential solutions.

Assuad et al. [3] proposed a framework that integrates Additive Manufacturing (AM) and Cyber-Physical System (CPS) for reconditioning practices. Although limited to reconditioning only, it is interesting, as the reconditioned systems are synchronized with conventional manufacturing process. Caterino et al. [4] proposed a novel approach, called Cloud Remanufacturing. Their framework is based on the integration of several Industry 4.0 technologies (Cloud Computing, Block Chain, Digital Models, etc.) to realize a centralized managed platform. However, it still needs to be validated in real context. Also based on Cloud Remanufacturing, in [5] the authors proposed a framework for complexity measurement and end-of-life (EOL) product adaptation on remanufacturing context. It is particularly suitable with assembly/disassembly processes. Assembly/disassembly process and complexity measurements have been also considered in Greco et al. [6], where a novel methodological framework is proposed to support technology selection, based on complexity, with the prospect of future remanufacturing. Other works, however, focus on the so-called Design for Remanufacturing (DfRem) to improve the remanufacture of EOL products. For example, Zhang et al. [7] included failure feedback and polychromatic sets theory into the product's design process, proposing a novel Reverse DfRem framework.

To enhance the effectiveness of remanufacturing, various works integrated technologies and methodologies into the process. Reverse Engineering (RE) and Additive Manufacturing (AM) are particularly prominent among these technologies. The former is focused on the 3D reconstruction to identify the damaged areas of the investigated parts [8] or to support the decision-making process in remanufacturing [9]. The latter is widely used to repair or to *as-is* reconstruct damaged parts [10, 11].

However, AM is mainly used for remanufacturing metal parts, ignoring the potential of other AM technologies, such as FFF, capable of sometimes printing plastics suitable with metal replacement.

Despite the existence of numerous applications and approaches to remanufacturing in the literature, the integration of essential technologies like RE and AM into the decision-making process is frequently highlighted. However, other significant aspects, such as the potential for reusing investigated components or redesigning them to enhance performance, are often overlooked.

This paper presents a framework that combines RE and AM to facilitate decision-making in remanufacturing damaged parts, encompassing options such as reuse, reconstruction, and redesign. A case study, considering a damaged component of a transmission system, is proposed to show the potentialities of its application.

The proposed framework serves as a foundational step towards the development of a comprehensive data-driven methodology. This methodology will aim to automate the analysis process and optimize strategy selection, resulting in improved outcomes in terms of cost savings, resource utilization, and environmental impact. By leveraging this framework and future advancements, remanufacturers can achieve greater efficiency and sustainability in their operations.

2 Methodological Framework

This section proposes a novel RE-based decision-making methodology to manage used products and to include AM in RMfg and re-design processes. Figure 1 shows the proposed methodological framework. Involving a process of 3D reconstruction of the investigated parts, through RE techniques, the methodology consists of two decision-making modules: the AS IS module (purple box) and TO BE module (green box). The AS IS module concerns the decision about the reworking worn products (as-is design), while the TO BE module is for developing new AM-based design of the product (to-be design). Used products can be collected in different way through reverse logistic networks. Specifically, they can be collected by the original manufacturer (manufacturing take-back or “In-House remanufacturing”), by a third-party remanufacturing provider (third-party take-back “outsourcing remanufacturing”) or by a retailer (retailer take back).

The core of the framework is based on the use of Reverse Engineering, for instance, through 3D laser scanning, for inspection aimed at identifying any defects or faults. Downstream of the entire Reverse Logistics process, which also includes disassembling the system under examination and an initial visual inspection, the 3D model of the investigated components is reconstructed from clouds of points acquired through laser scanning or other techniques (light blue box–Reverse Engineering). Using appropriate Artificial Intelligence (AI) algorithms, it is possible to identify the areas with defects/damage and, therefore, quantify the damage before proceeding with the decision-making process.

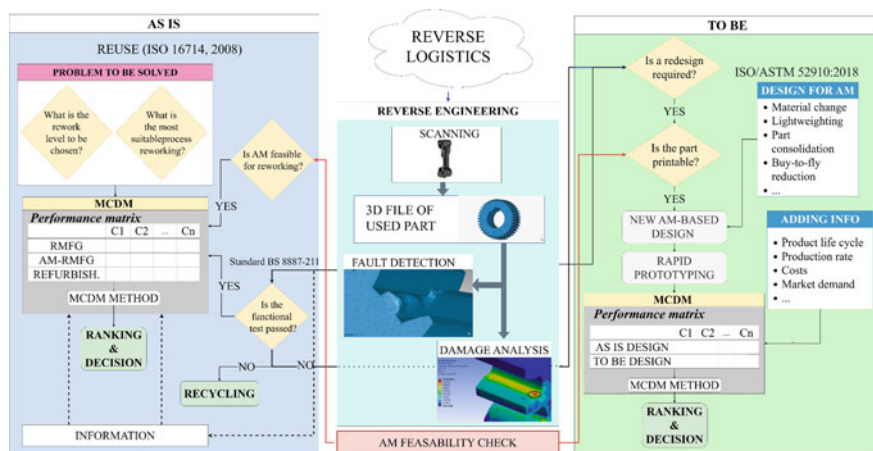


Fig. 1 Methodological framework

This methodology is intended to be applied in the context of manufacturing take-back or at most in the case of third-party take-back. In the latter case the remanufacturing provider is paid by the Original Equipment Manufacturer (OEM) to recycle and remanufacture waste products, while the OEM still get the selling rights. It was demonstrated that the choose of the remanufacturing strategy is strictly connected to the profitability of remanufactured products, the product quality, and the government policy [12].

2.1 AS IS Module

The problem to be solved in the AS IS module is contained in two main questions: (i) What is the rework level to be chosen? (ii) What is the most suitable process for the reworking? The EU defines reuse as “any operation by which products or components that are not waste are used for the same purpose for which they were conceived” [13]. Here, reuse includes operations as remanufacturing and refurbishment.

Once the part has been collected, disassembled and cleaned, it enters the RE module (light blue box), where 3D reconstructed model of the part is used to identify and quantify the damages. The results of this analysis are the input information of the decision-making process. If the part does not pass the functional tests [14], it will be recycled (or disposed), otherwise the decision-making process can start. Contemporary, the feasibility of AM as possible alternative for the reworking is checked (red line). If the check is positive, AM will be counted among reworking processes. A Multi-Criteria Decision-Making approach is adopted to solve the problem. The input of almost all MCDM methods is the *performance matrix*: alternatives are characterized by the values, or scores, assumed by a defined set of criteria. The alternatives

are all the potential reworking process among the RMfg, refurbishment and AM-based RMfg. Criteria are chosen by the decision-maker(s) according to the company strategic vision (Sect. 2.3), the knowledge of the process and the available time for the analysis. A proper MCDM method is implemented to rank the alternatives. The findings will be adopted by the decision-maker as a support to answer the main questions of the module.

The decision-making process is further enhanced by the support of simulation as a tool for functional verification of the investigated part, both for potential reuse and as-is reproduction. In terms of structural performance evaluations, CAE (Computer Aided Engineering) analysis tools incorporate simulation techniques based on FEM (Finite Element Method) or multibody simulation.

2.2 *TO BE Module*

The *TO BE* module is for developing new AM-based designs. The standard ISO/ASTM 52,910:2018 [15] gives guidelines and recommendations to design for AM. Material change, lightweighting, the opportunity for part consolidation and buy-to-fly reduction are some of the benefits deriving from the exploitation of AM. When the worn part comes back to the manufacturer, it passes through the RE module. Results from the RE module could suggest to redesign the product for improving its performance (dotted black line) over the lifecycle. Moreover, if the part is found unrecoverable, the redesign could be required to enable and/or simplify reworking operations (blue line). If the redesign is considered, the printability of the original part is checked as for the *AS IS* module (red line). Checking the printability simply concerns to verify whether the kind of product (size, geometry, material and value) is suitable for the printing. Nowadays, there are commercial software that support designers to perform this test. If the check is positive, the redesign process starts. Several AM-based designs can be obtained from the redesign activities. AM allows to rapidly assess the final product. The decision-making process regards the choice between the as-is design and the to-be design. This choice does not depend only on the product features but is function of multiple factors about the product life cycle, the production rates, costs and the market demand.

2.3 *Decision Criteria*

The decision-making process consists in determining the most consistent trade-off alternative according to the preference structure of the decision maker(s). Decision alternatives are compared through a set of criteria. The selected criteria can be qualitative or quantitative performance metrics. Wang et al. [16] identified four factors to be investigated in the field of the reverse logistics: quality, sustainability, economy and risk. These factors represent macro-criteria that can be broken down into several

sub-criteria depending on the level of detail of the analysis and the knowledge of the processes. Alternatives, criteria and measurements make up the performance matrix that represents the input of the Multi-Criteria Decision-Making method. Figure 2 represents a feasible hierarchy of the criteria.

The quality of used parts can be quantified by determining the damage level and their remaining useful life. According to Li et al. [17] and Wang et al. [16], it is possible to associate a damage score intervals to the kind of fault (e.g. wear, and deformation, corrosion and crack) and the corresponding volumetric damage interval. The remaining useful life can be determined by exploiting the failure and sensor data (if they are available). The decision must consider both environmental and economic sustainability. The energy consumption and further negative environmental impacts (e.g. global warming, ozone depletion, resource depletion) during the rework process can be quantified through a detailed Life Cycle Assessment (LCA) analysis or similar methods. The cost of the rework process can be estimated based on the *i*-th unit rework processing cost (*c*) and the time (*t*) required by the process:

$$C = \sum_i c_i t_i \tag{1}$$

However, the set of performance criteria can be tailored to the specific product, the industrial field and the strategy of the company.

The risk has a dual nature, meaning it could be the performance degradation risk of returned components, and/or the risk linked to the demand of used products. The first risk strongly depends on the environmental condition in which returned used products are stored. The latter risk is directly proportional to the market price of remanufactured products.

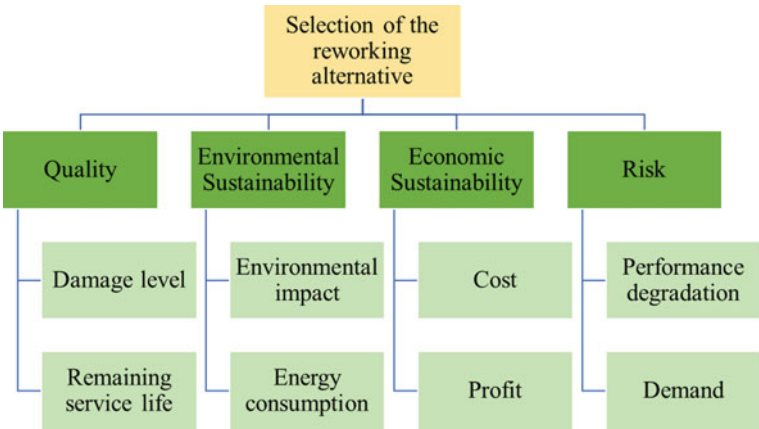


Fig. 2 Possible criteria of decision-making for reverse logistics and reworking [16]

3 Application Case

The primary objective of the provided case study is to demonstrate the practical implementation of the core of the framework outlined in Sect. 2 (light blue box-Reverse Engineering), focusing on the accurate identification and quantification of damage based on the mesh model of the impaired component, obtained through 3D laser scanning. The subject of investigation in this study is a spur gear that forms a part of a gear-box. Figure 3 illustrates the cloud of points of the damaged component reconstructed model, where several defects/damages are circled in red.

Starting from the STL model of the gear, first, a section regarding the identification and quantification of damage will be presented, which serves as a decision-making criterion for the remanufacturing of the part. Subsequently, the feasibility analysis process of additively manufacturing the component will be shown.

3.1 Damage Identification and Quantification

The damage identification phase has been approached with an Outlier Detection analysis based on a simple preliminary unsupervised machine learning algorithm. As a matter of fact, considering the damaged model showed in Fig. 3, it is clear that the damaged areas represent areas of outlier data, if compared to the undamaged ones. Moreover, the available data (namely, the coordinates of the meshed model elements' vertices and the direction cosines of the elements themselves) are unlabeled. This means that there is no additional information about the fact that some geometrical data may refer to damaged areas or not. In this framework, to detect anomalies in an unlabeled dataset, one popular approach is based on using Outlier Detection algorithms, belonging to the family of unsupervised machine learning algorithms. These algorithms aim to identify data points that significantly differ from the majority of the data and are, therefore, considered as anomalies or outliers.

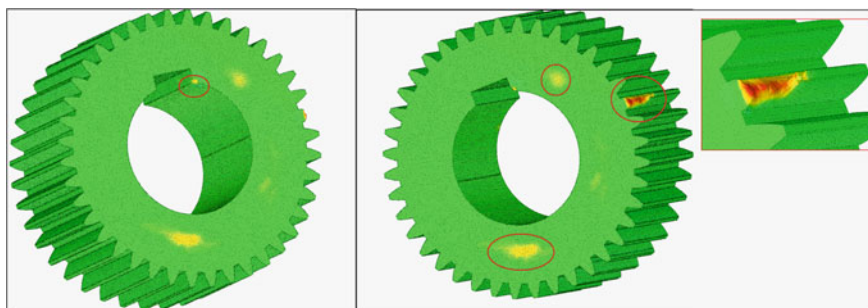


Fig. 3 Damaged gear reconstructed model. Defects/damages are circled in red

In the present case, the Isolation Forest algorithm [18], which is an efficient and effective algorithm for outlier detection, has been implemented. The Isolation Forest (IF) algorithm is based on the principle that anomalies are rare and more isolated than the normal data points; therefore, this approach is particularly effective for high-dimensional datasets and can efficiently detect anomalies without the need of labeled data. The key idea behind the IF algorithm is to construct isolation trees to isolate anomalies from the rest of the data points. An isolation tree is a binary tree structure where each internal node represents a feature, and each leaf node represents an instance from the dataset. The algorithm constructs these trees by randomly selecting a feature and a split value to partition the data into two branches until each branch contains a single instance or the maximum tree height is reached. The path length from the root node to the leaf node in an isolation tree can be used as a measure of how isolated a data point is. The intuition is that anomalies can be isolated more quickly, requiring fewer splits, than normal data points. The shorter the path length of a data point, the more likely it is an anomaly. As soon as the algorithm finds an anomaly, it assigns a label of -1 to the anomaly itself while it assigns 1 to the normal data points. Once the labels have been assigned, it is possible to easily visualize labeled data and discriminate between anomalies and non-anomalies. However, the effectiveness of anomaly detection depends on the quality of features and the choice of the algorithm's hyperparameters.

In this case, the tuning of the IF algorithm has been carried out by varying the so-called Contamination Parameter (CP), which heavily depends on the characteristics of the dataset and on the percentage of expected anomalies. In detail, by writing a code in Python[®] language in an Anaconda environment, the IF algorithm has been fitted on the dataset obtained from the gear's meshed model; the dataset consisted in six columns, *i.e.*, the *features*, containing the (X_g, Y_g, Z_g) coordinates of the triangular elements' centroids and the (v_1, v_2, v_3) direction cosines of the triangular elements' normal vectors. The fitting phase has been carried out by varying the CP from 0.01 to 0.05 with a 0.01-wide step. This means that it has been supposed that the anomalies represent a percentage which may vary between 1 and 5% of the total dataset. Once the CP is set, the IF algorithm tries to fit on data and to assign the data itself the label " 1 " (normal) or " -1 " (anomaly). The results are showed in Fig. 4 for the different chosen CPs.

In each subplot, the model of the gear is represented; in particular, it is made of points which are the centroids of each triangular element of the meshed model. The black points are the points classified as *normal* (*i.e.*, labeled as " 1 "), while the red ones are the points classified as *anomalous* (*i.e.*, labeled as " -1 "). It can be noticed that, even starting with a low CP (Fig. 4a), the damaged areas in correspondence of the two opposite plane faces of the gear are easily highlighted by the algorithm. In addition, the more the CP grows, the more the damaged areas are clearly defined.

However, the only damaged area that the IF algorithm struggles to identify is the one in correspondence of the gear tooth. As a matter of fact, due to the complex geometry of the gear teeth profile, as soon as the CP reaches slightly higher values (like 0.05, see Fig. 4e), the algorithm identifies as anomalous not only the damaged tooth, but, in general, the complex geometry of all teeth. For this reason, the IF

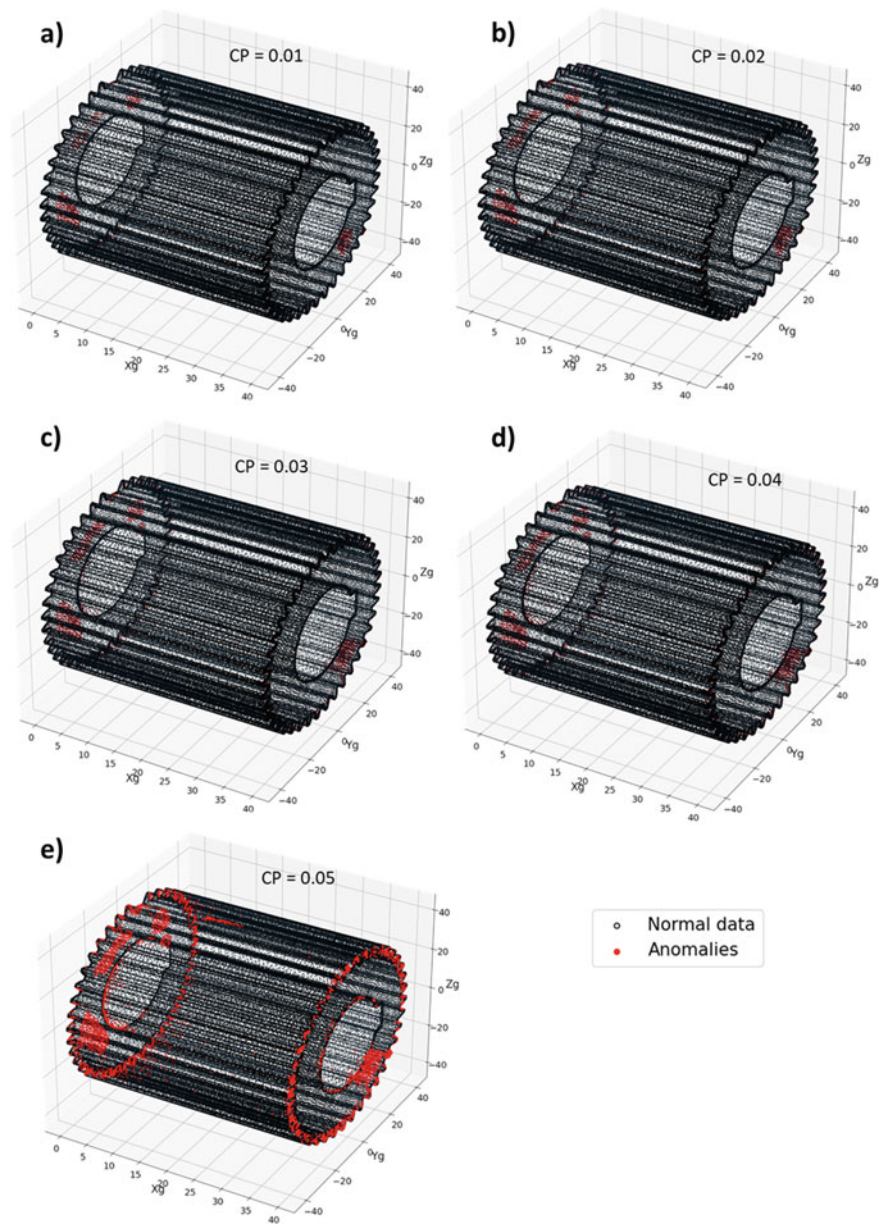
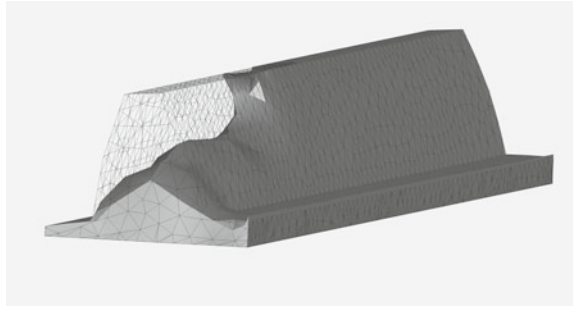


Fig. 4 Results obtained after the implementation of the IF algorithm for CP equal to 0.01 (a), 0.02 (b), 0.03 (c), 0.04 (d) and 0.05 (e). The black points are the ones classified as “normal”, while the red ones are the points classified as “anomalous”

Fig. 5 Meshed model of the sole damaged gear tooth



algorithm is promising and provides good results. However, for the detection of complex-geometry anomalies it surely needs to be further fine-tuned. In addition, as the presented approach is mainly based on the detection of geometrical anomalies, which are directly connected to the meshed model characteristics, this preliminary study sets the path for investigating how the meshing phase could possibly be improved and refined.

For future developments, the portion of the total missing volume belonging the damaged parts compared to the entire gear volume and the portion of missing volume of the sole tooth, compared to the volume of the original healthy tooth, have been computed. According to [16], the portions of missing volume are fundamental for better quantifying the damages entity. In this framework, it has been computed that the volume of the missing parts is the 0.24% of the gear's total volume, while the missing volume of the sole tooth is the 11.34% of a single tooth's volume (a graphical representation of the damaged tooth is showed in Fig. 5).

The volume calculations were carried out by means of the software Geomagic Wrap[®] but, for near future developments, this task will be hopefully given to machine learning algorithms as well. As a matter of fact, the final aim of this study is reaching the complete automation of the entire process of damage assessment, identification and quantification.

3.2 *AM Feasibility Analysis*

In the light of the results showed in the previous Sect. 3.1, if the damaged parts are so consistent to lead to the replacement of the entire gear, a feasibility analysis is mandatory. The feasibility analysis of 3D printing of the re-manufacturable parts is crucial to evaluate whether adopting this technology is appropriate for the project at hand. For the application case here-in adopted, the software 3D CASTOR[®] by Castor Technology Ltd has been used to assess the printability of the gear.

In CASTOR, the AM feasibility analysis includes several crucial factors, such as geometrical complexity, tolerances, costs, times, strength. Moreover, the analysis considers all the suitable materials and technologies that can be used for the production, providing a solutions map.

Based on the CAD model of the intact part and considering its original composition of AISI 1020 carbon steel, in the hypothesis of gear replacement, an investigation was conducted to assess the printability of the part. Involving a wide database of 3D printers and AM materials, the cost/material strength-based solution map (Fig. 6) revealed the optimal printing solution for the part. The selected replacement material is 17-4PH Stainless Steel, known for its strength of 907 MPa. The SLM-280 2.0 printer will be utilized for the implementation of this replacement.

The software utilizes the building orientation of the part on the printing plate to estimate the cost and delivery time, enabling a comparison with traditional production technologies like CNC and casting. For a sparse, flat-printed part, the estimated production time is 4 days (compared to 31 days with CNC) with an estimated cost ranging between \$774 and \$949. This cost includes printing expenses (\$242–348), post-processing (\$146), and supply chain costs (\$384–453).

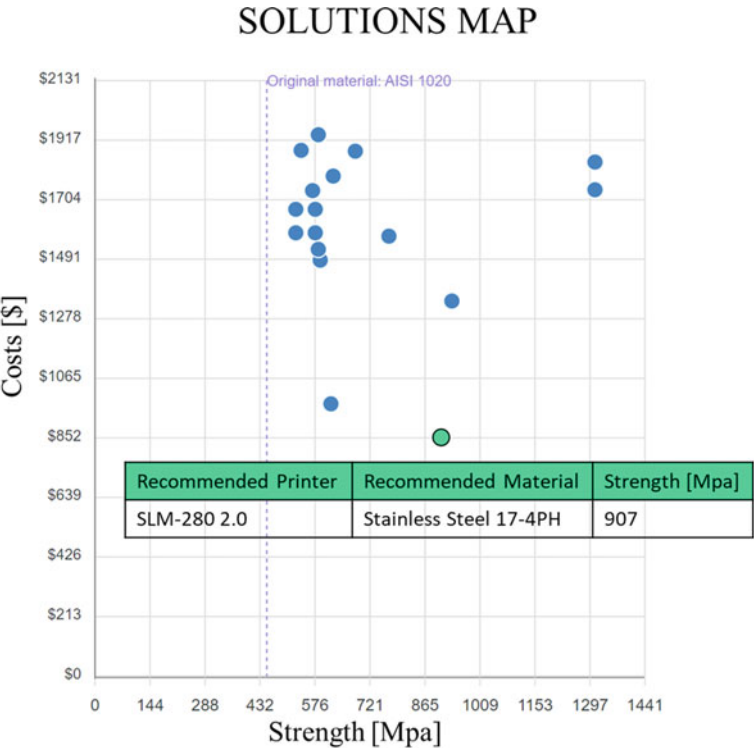


Fig. 6 Solutions map by 3D CASTOR

Additional investigations can be conducted on the geometrical characteristics and stress analysis by varying the building orientation and considering the operating loads. In the current case, no critical issues related to geometry or stress concerns were identified. Moreover, the analysis highlights the potential for reducing the part's weight, potentially through a redesign. These aspects and possibilities will be explored in future research.

Based on the AM feasibility analysis, it can be deduced that the technology is highly suitable for additively producing the component, despite not being the most cost-effective option. The major advantage lies in significantly reduced production times, approximately 80% shorter than those required for traditional manufacturing methods (*i.e.*, CNC). This aspect is critical as it allows for rapid restoring of the system's functionality, presenting a valuable opportunity in remanufacturing.

4 Conclusions

This paper aimed to propose a methodological framework supported by the combined use of Reverse Engineering (RE) and Additive Manufacturing (AM) to facilitate the multi-criteria decision-making process in remanufacturing. Starting from 3D models of damaged parts, reconstructed through laser scanning, it becomes possible to objectively identify and quantify the damages. Together with an analysis of AM feasibility, this provides crucial support in selecting the best remanufacturing strategy (reproduction, repairing, recycling, re-design, etc.).

A case study involving a damaged spur gear was presented to demonstrate the effectiveness of damage detection and quantification, based on exploiting the capabilities of unsupervised machine learning anomaly detection algorithms, as well as to detail an AM feasibility analysis considering all the critical aspects it encompasses. Near future developments will deal with a better quantification of the damaged parts in order to completely automatize the process of damage assessment, identification and quantification.

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Development of Depositions Strategies for Edge Repair Using a WAAM Process



Francesco Baffa, Gustavo H. S. F. L. Carvalho, Giuseppe Venturini,
and Gianni Campatelli

Abstract Remanufacturing is an industrial process which aims to restore a component to at least its original performance, and it is considered a key processes to support the transition to circular economy. For restoring a metal component, additive manufacturing processes based on Direct Energy Deposition (DED) techniques are the most widely used, because they can process a damaged part with a complex geometry. Among these, Wire Arc Additive Manufacturing (WAAM) has several advantages including a high deposition rate, lower operative, material, and equipment costs. Nevertheless, it is also characterized by low accuracy and a high risk of defects if the process is not tuned correctly. It is therefore crucial to develop effective deposition strategies to ensure defect-free deposition and high efficiency. This study focuses on the repair of edges of steel made components, and specific toolpaths has been designed and tested for repairing this geometrical features, both concave and convex, coupled with the selection of proper welding parameters and torch tilting angle.

Keywords Wire Arc Additive Manufacturing (WAAM) · Circular economy · Remanufacturing

1 Introduction

Circular Economy appears to be one of the main approaches adopted to address the issue of sustainability [1]. In addition, Covid-19 pandemic has also highlighted supply chains fragility, especially in Europe, thus the necessity of more resilient supply system [2]. In industry, the issues of sustainability and resilience have found a meeting point in the circular economy, as a possible strategy for simultaneously reducing waste (and therefore reducing the environmental impact) and dependence on external suppliers (increasing resilience of supply chains). Aim of circular economy is to decouple growth and resource consumption and sometimes it is summarized as

F. Baffa (✉) · G. H. S. F. L. Carvalho · G. Venturini · G. Campatelli
Dipartimento di ingegneria industriale, Università degli studi di Firenze, Via di Santa Marta, 3,
50139 Florence, Italy
e-mail: francesco.baffa@unifi.it

“doing more with less”. In the manufacturing field, it means to keep the product—or at least its material—as much as possible within the boundaries of the manufacturing system. Russell and Nasr defined five processes, called Value Retention Processes, which aim to preserve the value acquired by the component from the extraction phase to the use phase: Direct Reuse, Repair, Refurbishment, Comprehensive refurbishment, and Remanufacturing [3].

Transition to circular economy therefore involves many aspects, for industries these concern mainly supply chain management, product design, and implementation of recovery operations.

This study focuses on remanufacturing, an operation whose aim is to restore (at least) the initial performance of the worn product. The remanufacturing process involves many stages: disassembly, cleaning, inspection, repair, replacement, reassembly [4]. The repairing phase essentially involves only technical aspects, thus is the most technologically challenging. From a technological point of view, the repair phase presents the greater technical difficulties. This project focuses on the development of repair strategies able to achieve a high-quality repaired part for a metal component through a hybrid process based on Wire Arc Additive Manufacturing (WAAM) and machining. For remanufacturing operations, Additive Manufacturing (AM) technologies are particularly suitable. Among these, the most suitable ones are Direct Energy Deposition (DED) techniques, as they have the possibility of working on the pre-existing part, that it is precluded to powder-bed solutions. WAAM has the advantages of a high deposition rate, a wide choice of materials, an easy management of the filler material, a lower cost of the material, and a lower cost of equipment. Moreover, it presents fewer health issues since it uses metal wire instead of metallic powder [5].

In the last years, also another feature of WAAM has increased its interest for the users: its reduced environmental footprint respect to its main competitor, i.e. AM based on laser as source and metal powder as feedstock [6], since both the production of the filler material and the process itself are less energy-intensive. Nonetheless, WAAM has the disadvantage of a lower accuracy and it is characterized by typical defects: porosity, high residual stress levels, and cracking [7]. As remanufacturing often deals with non-standard components, it is necessary to develop process strategies able to guarantee the correct deposition of the beads of new material. Industrial sectors where repairing process are significantly adopted are turbo-machinery [8], dies and molds [9], and marine transportation [10]. However, the most adopted technologies are based on laser and metal powder.

The remanufacturing process of a metal component by means of AM essentially consists of three stages [9]:

1. First machining phase: worn and damaged material is removed, and a geometrically known shape of the surface is obtained.
2. Deposition phase: new material is added through AM technique to restore the worn features.
3. Second machining phase: exceeding material is removed, and the final geometry is achieved.

Fig. 1 Welding torch mounted on the milling center



Therefore, additive process is just one of the three main phases of the remanufacturing operation. The significant presence of subtractive phases justifies the adoption of a hybrid process, that integrates in the same machine both machining operations and additive manufacturing. This choice has several advantages, among them the streamlining of setup operations.

This study aims to develop a remanufacturing strategy for metal components through a hybrid process based on WAAM, including toolpath, torch inclination and deposition parameters.

2 Material and Methods

The equipment adopted for repairing operations is a hybrid machine, realized by retrofitting a 5-axis machining center DMG Mori DMU 75-Monoblock. A special tool that supports a GMAW (Gas metal Arc Welding) torch has been designed and implemented in the automatic tool changer of the machine in order to alternate quickly and smoothly milling and WAAM operations (Fig. 1). The welding machine is a Fronius TPS 320i able to perform GMAW in different modes, e.g. Cold Metal Transfer (CMT) and Low Spatter Control (LSC) [11]. Mild steel has been adopted both for substrate (made by S235JR) and wire feedstock (ER70S-6). Shielding gas mixture is made of 82% Ar and 18% CO₂. Substrate and wire composition are listed in Table 1.

Table 1 Chemical composition of the wire and the substrate; reported data are from producers' data-sheets

	C%	Mn%	Si%	P%	S%	Cu%	Fe%
Wire	0.08	1.5	0.9	≤0.025	≤0.025	–	Bal.
As deposited	0.08	1.1	0.6	≤0.025	≤0.025	–	Bal.
Substrate	0.19	1.5	–	0.045	0.045	0.45	Bal.

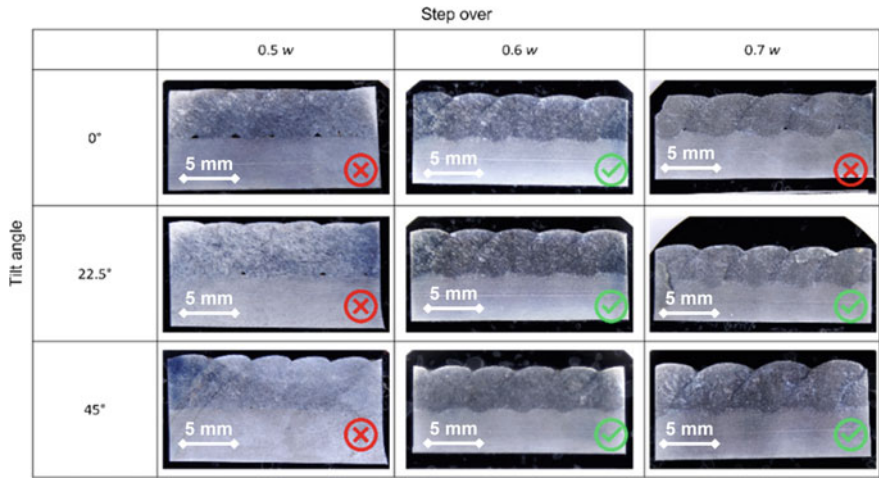


Fig. 2 Overview of material voids assessment. The parameter w is the bead width

Repairing operations usually involve reconstruction of solid features (e.g. a gear tooth) or surfaces cladding (e.g. in case of a worn mold). WAAM cladding processes are much less studied in literature, and they have a potential risk for some quality issues. Two of the most common defects that occur when cladding a surface are the lack of material in correspondence of the undercut zone of the two adjacent beads and the material stacking due to a too low stepover between two beads. To solve these issues, bead modeling has been studied extensively in literature for defining the optimal stepover value to obtain a planar surface and to avoid defects between adjacent beads. These models, namely Beads Overlapping Models (BOM), express the stepover value as function of beads' width and different coefficient are due to different geometrical shape adopted for describing beads cross section. Important BOM exploit circular arc [12], parabola [13, 14], and sine function [15].

However, most of the results are specific for traditional pulsed GMAW, that is characterized by a high heat input, that usually must be avoided since it is responsible for residual stresses on the component. The optimal solutions for welding techniques with lower heat input, such as CMT [16], still must be further investigated. The presented study wants to take advantage also of the effect of inclination angle of

Table 2 Parameters adopted for tests grouped by similar bead width

Test (–)	W_{ref} (mm)	Current (A)	Voltage (V)	WFS (m/min)	WS (mm/min)	HI (kJ/mm)	AP (kW)
1	6.5	130	21.1	12	600	0.274	2.74
2	6.7	91	18.9	8	400	0.258	1.72
3	6.7	11	20.2	10	500	0.269	2.24
4	6.8	179	27.4	20	1000	0.294	4.91
5	7.8	114	20.0	10	300	0.456	2.28
6	7.9	119	20.1	10	400	0.359	2.39
7	8.0	150	22.1	14	500	0.398	2.31
8	8.1	92	20.8	8	200	0.574	1.91
9	8.2	138	21.2	12	400	0.439	2.93
10	9.1	152	21.7	14	400	0.495	3.30
11	9.2	117	19.7	10	200	0.691	2.30
12	9.3	124	22.5	12	300	0.558	2.79

the torch, namely tilting angle, on cladding a surface, as it allows quality improvement [17], and to integrate it in the design of an effective strategy for repairing a surface. The results are summarized in Fig. 2. The inclination overcomes the difficulties related to undercut areas of adjacent beads, which also allows easier access to the torch, for filling milled pockets. Current activity is focused on repairing of edges, both concave and convex, since it is a very common feature that could be found whenever repairing a metallic part, e.g., a concave edge can be commonly obtained after the removal of the worn feature. The edges that have been included in this study are both sharp and chamfered.

First, different set of parameters have been tested on a flat surface, and their coverage of the worn surface has been measured to correlate this value when depositing on a plane and on an edge. Then, twelve sets of parameters were selected grouped by similar geometrical dimensions. They are listed in Table 2, reporting the electrical parameters, welding parameters, i.e. Wire Feed Speed (WFS) and Welding Speed (WS), and energy input, i.e. Arc Power (AP) and Heat Input (HI). AP and HI are calculated as follow:

$$AP = \frac{V \cdot I}{1000} \quad (1)$$

$$HI = 60 \cdot \frac{AP}{WS} \quad (2)$$

Numerical coefficients are needed to give AP in kW and HI in $\text{kJ} \cdot \text{mm}^{-1}$.

As shown in Fig. 3, deposition on the edges is performed rotating—by mean of the tilting table—the work piece by 45°C and putting the welding torch on the bisector of the edge angle. For analyzing concave edges has been measured height (h), bead sides (L_1 and L_2), the bead area (A_b), the area added to the pre-existing

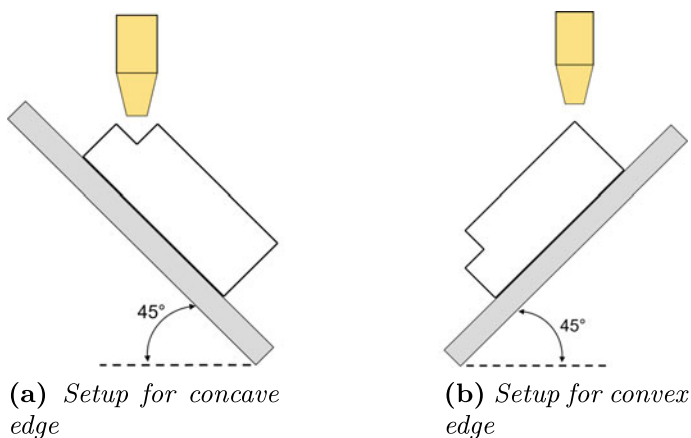


Fig. 3 Different setup for edge features

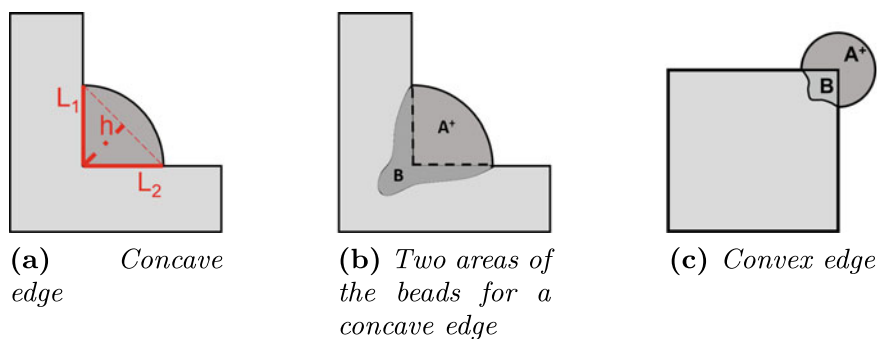


Fig. 4 Representation of the beads' measures

geometry (A^+), and dilution (D). Similarly, A_b , A^+ , and D has been measured for convex edges. A geometric representation of the measures is shown in Fig. 4, while the dilution has been calculated according to Eq. (3):

$$D = \frac{A_b}{B} \cdot 100 \quad (3)$$

Where B is the part of the bead penetrated in the substrate (Fig. 4). For observing the tests after the deposition, standard metallurgical techniques have been followed. Test specimens were prepared by cutting, mounting in epoxy resin, grinding, and polishing with abrasive paper up to 1200 grit. Nital (1% nitric acid and ethanol mixture) was used as etching solution.

Table 3 Data from deposition on concave edges

Test	L_1 (mm)	L_2 (mm)	h (mm)	A_b (mm ²)	A^+ (mm ²)	D (%)
1	4.7	4.7	3.5	15.1	11.1	26.1
2	3.7	5.0	2.7	11.5	9.0	21.5
3	4.4	4.1	2.9	10.8	9.4	13.7
4	5.0	4.1	3.0	15.9	10.1	36.4
5	6.1	5.4	4.0	19.8	17.5	11.5
6	4.9	4.5	3.3	17.4	16.3	6.5
7	5.1	5.3	3.6	20.0	17.8	10.9
8	6.1	5.9	4.1	21.0	19.8	5.6
9	5.2	5.3	3.6	17.7	14.2	20.1
10	5.3	5.9	3.9	21.4	17.0	20.6
11	8.2	6.3	4.9	27.7	26.2	5.5
12	5.3	7.8	4.2	26.8	20.6	23.1

3 Results

Results of deposition are listed in Table 3 for concave edges and in Table 4 for convex edges. It could be notice that there is not a clear correlation between the value of the reference width of the beads deposited on a plane and the mean value of L_1 and L_2 . This is probably due to the different heat input that is responsible for a variation in substrate melting and the aspect ratio (width-height) of the bead and different thermal conductivity for convex and concave geometries, as shown in Fig. 5. Specimens in Fig. 6 show this issue. Nonetheless, this correlation must be further investigated. It could be noted also a relevant variability in the value of L_1 and L_2 both for convex and concave edges. The variability could be assessed by calculating the residuals respect to the mean value, and this assume a value of 0.56 for concave and 0.97 for convex, that is nearly twice the value for concave.

Indeed, the deposition on a sharp convex edge could be source of uncertainty since the bead easily tends to a side or to the other. This would affect the subsequent cladding of the vertical and the horizontal side since the resulting geometry is undefined and this will create a lack or stacking of material with an automatic repairing cycle. This issue could be hardly solved since the instability of the arc on a sharp edge it is difficult to control and the measure of the deposited bead and the following adjustment of the toolpath for the deposition of the next bead is time consuming and avoid the implementation of an automatic repairing cycle. The solution that we are pursuing is to create a geometry before deposition that will reduce the variability of the bead position and geometry. This could be solved by introducing a 45 chamfer of different dimensions on the sharp edge where it is possible to deposit the corner bead on a flat surface. The initial tests had a single parameter set, and the width of chamfers is related to the bead width, as reported in Table 5.

Table 4 Data from deposition on convex edges

Test	L_1 (mm)	L_2 [mm]	A_b (mm ²)	A^+ (mm ²)	D (%)
1	4.3	4.5	15.6	9.0	42.3
2	2.4	4.8	14.3	9.3	35.0
3	4.8	4.1	16.3	8.7	46.6
4	4.2	4.0	17.6	8.1	54.3
5	4.3	6.0	25.1	14.4	42.7
6	3.2	5.4	20.1	11.2	44.4
7	4.3	5.9	25.0	13.1	47.7
8	5.1	5.3	26.9	17.9	33.4
9	2.4	6.1	19.9	10.9	45.2
10	7.0	4.2	28.7	16.9	40.9
11	5.6	6.7	36.5	23.7	35.1
12	6.8	5.1	32.2	19.6	39.1

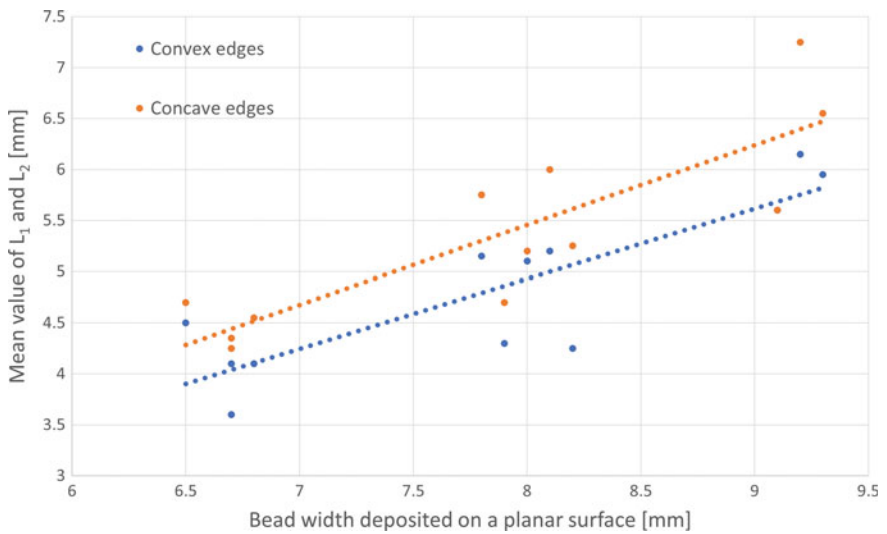


Fig. 5 On the horizontal axis are reported the beads' width on a flat surface, on the vertical the mean value of L_1 and L_2

Table 5 Chamfers cladding tests, d is the chamfer width, w is the bead width

Test	d	d (mm)	N of beads
1	$0.8 \cdot w$	4	1
2	w	5	1
3	$1.2 \cdot w$	6	2
4	$1.6 \cdot w$	8	2

Fig. 6 Uncertainty is more significant in case of convex edges

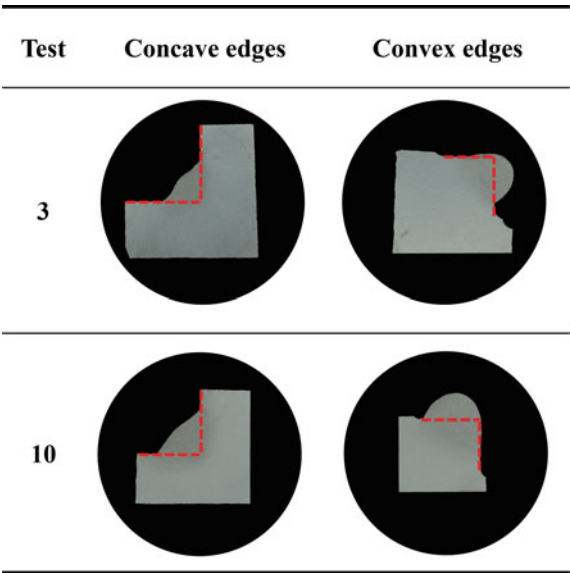
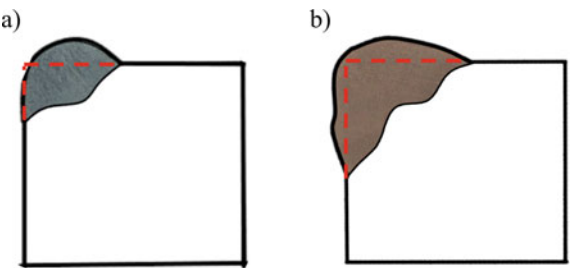


Fig. 7 Tests 1 a and 3 b of chamfered edges

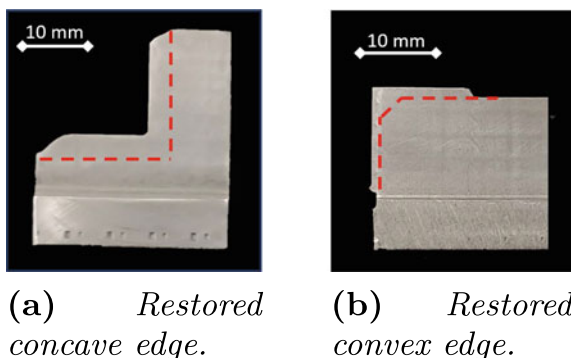


Deposition on chamfers requires one or two beads accordingly with their dimensions. A_b , A^+ , and D have been measured for these tests as well.

When two beads are needed for chamfer cladding the stepover was fixed at $0.6w$. Therefore, set the chamfer width at $1.6w$ means to set chamfer width equal to the overlapped beads width. This seems to solve the issue, in fact, the deposition with two beads on a chamfer narrower than the overlapped beads, shows quite promising results, with consistent deposition geometry. On a chamfer characterized by a width of $1.2w$, deposition is nearly symmetric, and beads cover the whole chamfer (Fig. 7).

As a final test, a few beads were deposited adjacent to the one in the concave edge and those deposited on the chamfer. As shown in Fig. 8, both strategies demonstrate that they achieve the goal of depositing material without lack of material.

Fig. 8 Edges after deposition of fresh material and removal of excess material



4 Conclusion

The restoring of convex edge is characterized by a high uncertainty of the deposition geometry that is often asymmetric, thus affecting the reliability of the process. A solution is the preparation of the surface by machining a chamfer that enable a more stable deposition process. These results could be exploited also to address worn edge repairing, that is removing the edge is mandatory. For instance for restoring the edge of a worn sheet-punch. On the other hand, deposition on a concave edge is less difficult, because the arc tends to converge at the edge itself. Starting from these preliminary results, some future actions could be planned, like fillets repair, where also the effect of the corner radius must be considered to predict the coverage of the surface and plan the position of the next beads accordingly. A model for fillets could be extended to repair free-form surfaces, that can be found, for instance, in molds and dies, which are a typical component subject to remanufacturing. Once the approaches to repair the most common geometrical features will be developed, it will be required to solve the issue of the connection of different toolpaths strategies to achieve a single and consistent remanufacturing cycle. In fact, a complex component could require different strategies for each of its features and these must be consistently and smoothly connected to avoid lack or stacking of material. In the meantime, also material tests need to be performed to ensure mechanical properties of the remanufactured parts. These tests could involve hardness test, grain analysis as well as tests for specific application, e.g. corrosion resistance assessment and thermo-mechanical properties. This final result will support a wider adoption of remanufacturing both for standard and non-standard components, ensuring at least the same performance of the original component and lower environmental impact and supporting the introduction of a greener manufacturing cycle.

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Finite Element Model of Structural Health Monitoring System Based on Ultrasonic Guided Waves on Remanufactured Components



Antonio Aversano , Antonio Polverino , and Giuseppe Lamanna 

Abstract Ultrasonic guided wave-based (UGW) structural health monitoring (SHM) is a sophisticated and invaluable process that employs an array of sensors and measurement devices to meticulously assess the ongoing performance and condition of various structures. Over time, accumulated data can facilitate the structural diagnosis, enabling informed maintenance decisions, and supporting remanufacturing efforts. SHM can play a key role in regeneration by providing valuable information on the condition of structures and components. This encompasses its capacity to ascertain the feasibility of remanufacturing, guiding determinations regarding the salvaging of reusable parts as opposed to the replacement of those that no longer meet operational standards. Moreover, SHM excels in its ability to pinpoint damage within structures and components, meticulously monitor the performance of remanufactured components, and ensure their alignment with predefined performance criteria. In this work, a finite element (FE) model of UGW-based SHM system on a aluminum plate, in pristine, damaged and remanufactured conditions, is presented. Notably, the wealth of SHM data gathered throughout the remanufacturing process can be strategically leveraged to refine the design of components and structures in subsequent iterations, thereby perpetually advancing the overall quality and efficiency of remanufactured products.

Keywords Guided waves · Structural health monitoring · Remanufacturing

1 Introduction

To enhance the safety and durability of structures, the engineering community is actively exploring innovative sensing technologies and analytical approaches to swiftly detect and track damages in instrumented structural components, often

A. Aversano (✉) · A. Polverino · G. Lamanna
University of Campania “L. Vanvitelli”, Via Roma 29, 81031 Aversa, Italy
e-mail: antonio.aversano@unicampania.it

referred to as “smart structures”. Among these techniques, structural health monitoring (SHM) systems offer automated solutions for monitoring a structure state of health by means of damage detection algorithms [1–6]. SHM systems are created by either deploying separate sensors (passive method) or integrating sensors and actuators (active method) appropriately within structures. The adoption of SHM systems is closely tied to the principles of damage tolerance design [7]. Incorporating SHM systems during the design phase can reduce the life-cycle costs, replacing routine inspections with as-needed maintenance, leading to more precise and efficient repair operations [8].

This technology has numerous applications, including in the field of remanufacturing. Remanufacturing refers to the process of restoring used products to like-new condition, often involving disassembly, repair, replacement of components, and reassembly.

Incorporating SHM into remanufacturing processes can yield numerous advantages:

- **Assessment of the structural integrity:** SHM techniques, such as sensors, accelerometers, strain gauges, and acoustic emission sensors, can be employed to continuously monitor the condition of vital components during disassembly, repair, and reassembly. This ensures the detection of damaged or weakened parts, leading to improved overall remanufactured product quality [9];
- **Early Detection of Defects:** SHM can identify defects or wear patterns that might be missed in traditional visual inspections, mitigating potential failures or performance issues in the remanufactured product;
- **Data-Driven Decision-Making:** SHM generates data on component structural health and performance, facilitating data-driven decision-making throughout the remanufacturing process. Real-time data can inform decisions regarding component repair or replacement;
- **Optimized Resource Allocation:** SHM data offers insights into the remaining useful life of components, allowing for more efficient resource allocation. Components with substantial remaining life can be prioritized for repair, while those near the end of their life can be replaced;
- **Quality Assurance:** SHM ensures that remanufactured products meet or exceed quality standards by detecting defects or deviations from specifications;
- **Performance Monitoring:** SHM provides ongoing value after the remanufacturing process, enabling real-world performance monitoring of the remanufactured product and helping to identify any operational issues;
- **Regulatory Compliance:** in industries with strict safety regulations, integrating SHM into remanufacturing processes can aid in complying with safety and quality standards.
- **Cost Savings:** despite the initial investment in SHM technology, the long-term benefits include reduced maintenance costs, fewer unplanned downtime events, and enhanced customer satisfaction due to improved product reliability.

To effectively implement SHM for remanufacturing, the following guidelines should be met:

- **Assessment:** identifying the critical components that require monitoring, and then select the most suitable SHM techniques for your specific application;
- **Sensor Deployment:** installing the appropriate sensors and instrumentation on these components to continuously track essential parameters such as stress, strain, temperature, vibration, and acoustic emissions;
- **Data Collection and Analysis:** collecting and processing data gathered from sensors. This step permits the assessment of structural health, identifying anomalies, predicting their remaining useful life, and suggesting necessary maintenance actions;
- **Integration:** integrating the SHM data into your decision-making process during the phases of disassembly, repair, and reassembly. Set clear thresholds for deciding whether a component should be repaired or replaced, basing these thresholds on the insights derived from data analysis;
- **Continuous Monitoring:** extending the monitoring beyond the remanufacturing process itself. Continue to observe the real-world performance of the remanufactured product, utilizing this ongoing data to validate the effectiveness of your remanufacturing procedures and refine future strategies;
- **Feedback Loop:** Establishing a feedback loop that utilizes the wealth of SHM data to drive continuous improvement in your remanufacturing process over time. This iterative approach ensures that you adapt and enhance your practices based on real-world performance data.

2 Methodology

In this section, a numerical investigation of an aluminum plate under pristine, damaged, and remanufactured conditions is described. In this regard, FE models were used to better understand the propagation mechanisms in the presence of damage and after removing the damage by taking away material. UGW dispersive wave behavior can help designers to improve the effectiveness and damage sensitivity in remanufacturing perspective. The case of study consisted of a square-shaped aluminum panel, whose geometry is shown in Fig. 1. The plate has a side length of $L = 300$ mm and a thickness of $t_a = 1.6$ mm. The mechanical properties are listed in Table 1. The flat plate was then equipped with an array of two PIC255 piezoelectric sensors to generate guided/elastic mechanical waves and detect diagnostic signals. Transducer PZT1 worked as the primary actuator, while PZT2 was used as the sensing device. Specifically, the sensors were placed at a mutual distance of $L1 = 100$ mm. The distance between the PZTs and the edges of the flat panel is $h = 150$ mm. The schematic of the network of PZTs is shown in Fig. 1, whilst mechanical and electrical properties of the PZTs are reported in Table 1.

Fig. 1 Schematic of the PZTs arrangement

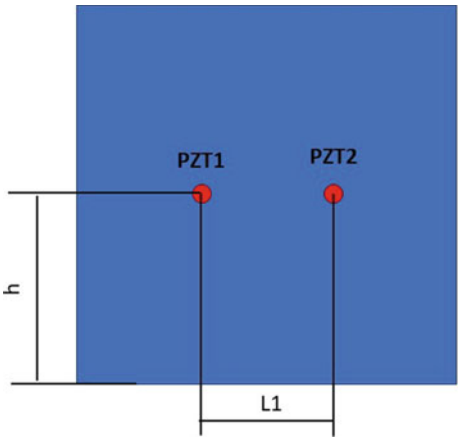


Table 1 Material properties

Material properties	Symbol	Units	Al 6061	PIC255
Mass density	ρ	$[kgm^{-3}]$	2700	7850
Young' s modulus	E	$[GPa]$	69	76
Shear modulus	G	$[GPa]$	26	29
Poisson's ratio	ν	—	0.33	0.32
Dielectric constant	K_3	—	—	1280
Piezoelectric charge constant	d_{31}	$[10^{-9}mmV^{-1}]$	—	−180

The plate was divided into discrete finite elements of type C3D8R (8-node element, with 3 degrees of freedom per node) with an average element size of 0.9 mm to accurately represent the plate’s behavior in the analysis, while the piezoelectric transducers (PZTs) were discretized with an average element size of 0.6 mm. The number of elements within the plate thickness is 8, whereas 2 for the sensor. The details of the FE modeling are given in the Table 2.

UGW excitation was modelled with a windowed tone burst signal consisting of 5 cycles at a central frequency of 200 kHz, as visible in Fig. 2a. Under a numerical point of view, to simulate the actuation signal, a prescribed displacement was applied to the nodes on the upper circumference of the sensors, as shown in Fig. 2b, according

Table 2 Numerical model properties

Instance	Element type	Number of nodes	Number of elements
Plate	C3D8R	815,409	719,895
PZT	C3D8R	1731	1080
Whole Model	C3D8R	818,871	722,055

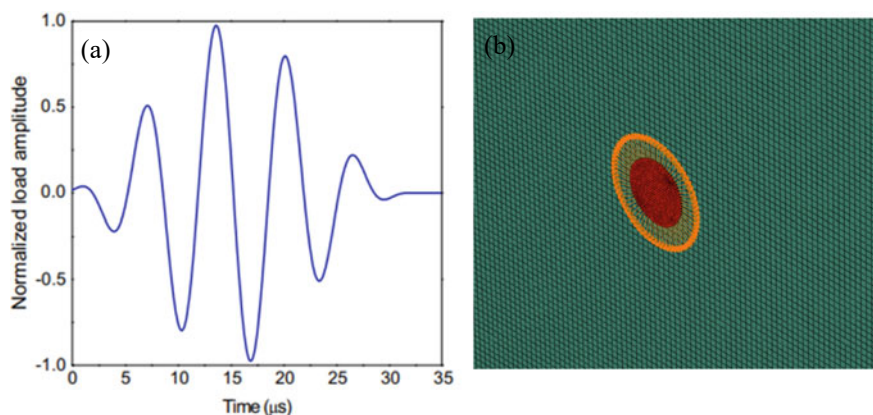


Fig. 2 Excitation signal (a), equivalent radial displacement field (b)

to the literature. A dataset of UGW signals was thus acquired in the reference, i.e., undamaged configurations of the panel.

To reproduce a damaged scenario, a surface damage was introduced into the model by deleting one layer of elements at a specific location, as visible in Fig. 3. Specifically, the damage has a square shape with dimensions $a = 3$ mm, and $b = 20$ mm and its thickness is 0.2 mm. It was positioned on the non-instrumented surface.

Then, to restore the plate to its original condition under the remanufacturing point of view, a metal cutting solution was considered. The entire set of surface elements (top layer) aligned with the depth of damage was removed (grey colored elements in Fig. 3).

It is noteworthy to underline that in both damaged and remanufactured panel configurations, UGW data was acquired.

3 Results Analysis

As previously mentioned, the signals captured by sensor 2 in the pristine, damaged, and remanufactured configurations were analyzed. Figure 4 illustrates how the signal amplitude varies for the three configurations. It can be observed that the presence of damage significantly alters the signal amplitude compared to the pristine and the remanufactured configurations. The structural discontinuity is particularly evident from the zoomed area of the plot.

The figure illustrates a significant impact on signal amplitude due to the presence of damage. From the comparison of the three signals gathered by the undamaged, damaged and remanufactured configurations, it is evident how the presence

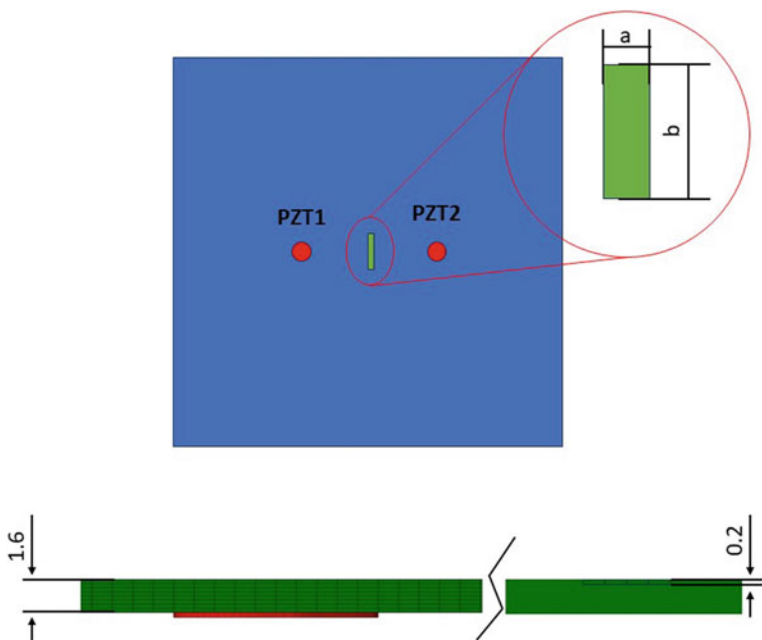


Fig. 3 Damage modelling

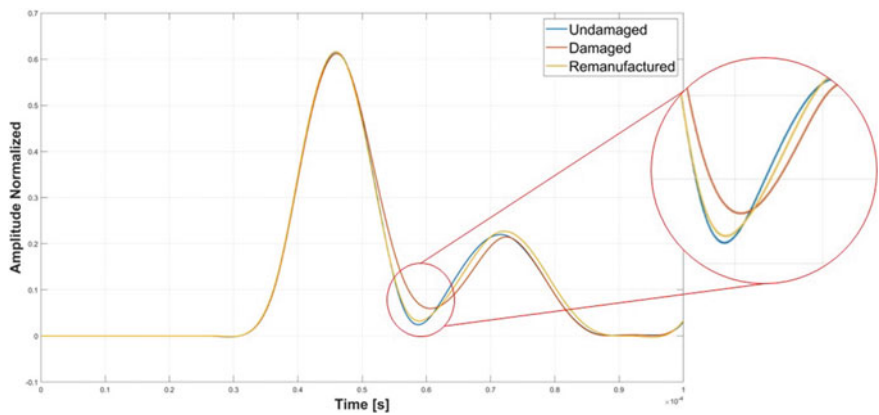


Fig. 4 Signals recorded at the pristine, damaged, remanufactured configurations

of surface damage influences the propagation of guided ultrasonic waves. Specifically, the difference in amplitude is greater in the presence of surface damage, and it decreases with the removal of the layer of elements corresponding to a 0.2 mm reduction in plate thickness. After an initial phase of numerical investigation, it can be concluded that the SHM system proves to be a valuable ally in remanufacturing, as

it is capable of providing information about the structural condition of the component both before and after processing. During the design phase, it may be advantageous to incorporate sensors within the components to enable the real-time, near-real-time, or scheduled “capture” of the component’s health status. This approach would provide the flexibility to make more informed decisions about when and whether to rework the component to restore it to its initial operational condition.

4 Conclusion

In this study, a finite element numerical model was developed to replicate a structural health monitoring (SHM) system based on guided ultrasonic waves in an aluminium plate. The numerical investigation was conducted on three different configurations: undamaged, with superficial damage, and regenerated. Signal analysis revealed that the presence of damage significantly affects the signal amplitude compared to the other two configurations. Specifically, it was observed that in the presence of damage, the signal amplitude deviates significantly from the signal obtained when the plate is intact and after reworking.

It can therefore be concluded that the use of an SHM system, installed during the design phase, in the context of remanufacturing, would be useful for obtaining information about the component’s health status both during operation and after processing.

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Integrating Remanufactured and 3D Parts in Asset Maintenance Improvement



James Wakiru and Peter Muchiri

Abstract This research aims to optimize asset performance by integrating spare parts replacement, remanufactured parts, 3D printed parts, and repair, corrective, and preventive maintenance. The study reviews the current asset maintenance practices and proposes a framework for integrating various maintenance and spare parts strategies to achieve maximum asset performance. The proposed framework considers the asset's criticality, the availability of spare parts, and the effectiveness of each maintenance strategy in influencing the reliability and useful life of the spare parts utilized. The research also explores the potential of using 3D printing technology to produce spare parts and remanufacturing as a sustainable alternative to buying new parts. A case study is conducted to demonstrate the effectiveness of the proposed framework in optimizing asset performance. The results show that integrating the various maintenance strategies can save significant maintenance time and improve asset performance. The study concludes that a comprehensive approach to asset maintenance that considers all available maintenance and spare parts strategies is essential for achieving maximum asset performance, reducing downtime, and improving the overall efficiency of asset management.

Keywords Remanufacturing · Maintenance · Spare · Inventory · 3D

1 Introduction

Asset availability is a critical factor that directly affects the profitability of an organization. Guaranteed asset availability ensures that a plant can meet customer demand and remain profitable. However, asset availability is affected primarily by unplanned failures and protracted lead times due to the wait for spares and other resources for maintenance. Hence, optimization of the maintenance of assets is essential to ensure that they remain functional and available.

J. Wakiru (✉) · P. Muchiri
Dedan Kimathi University of Technology, Nyeri, Kenya
e-mail: james.wakiru@dkut.ac.ke

The main maintenance strategies exploited in industrial facilities include Preventive maintenance (PM), which involves replacing parts after a pre-defined interval, and Corrective Maintenance (CM), which addresses unplanned failure or performance reduction. Under CM, various actions, such as replacement, repair, adjustment, and service, are defined and used [1]. A critical maintenance action cutting across both CM and PM is the replacement of the parts, where several options or alternatives for spare replacement are typically employed. The main alternative is usually the replacement using a new spare part, which provides benefits like renewed reliability and life [2]. Due to asset ageing and parts obsolescence, parts are remanufactured to extend their life. However, the uncertainty of the remaining useful life of a remanufacturable part and the uncertainty of the remanufacturing decision affect its exploitation in maintenance [3, 4]. On the other side, due to the remote geographic locations of many plants, access to spare parts is intermittent; hence, the use of new spare parts inflicts high extended sourcing lead times, directly affecting plant availability. Additive manufactured or 3D printed parts offer a localized solution as they are speedily and cost-effectively manufactured in remote locations. 3D parts have been used in such facilities and offered reduced lead times, offering a potential spare part replenishment solution [5]. To optimize the asset availability while considering the various maintenance strategies, CM and PM and the alternative spare parts replacement options simultaneously inherently should be undertaken to quantify the benefits; however, work that has involved 3D parts (e.g., in automotive [6], aircraft [7], maritime [8] and medical fields [9]) has not considered all the options simultaneously, hence may not provide the added value of the alternative options to asset maintenance and performance.

To address these challenges, this research proposes an integrated approach to asset maintenance that includes corrective (repair, reuse, replace and remanufacture) and preventive maintenance, where spare parts replacement alternatives, remanufactured parts, and 3D printed parts are integrated simultaneously. This approach aims to reveal the added value by optimizing asset availability while reducing maintenance time. This study proposes a discrete event simulation (DES) model framework that considers modelling a repairable system whose deterioration is assumed to follow a Semi-Markov Decision Process (SMDP). The design of the experiment (DOE) approach is utilized to quantify the effects and interactions of the variables on equipment availability and total maintenance time. DES is utilized due to its robustness in dealing with complex, highly variable and uncertain events as a decision support tool, also corroborated by [10].

The remaining part of the paper proceeds as follows: Sect. 2 presents a brief literature review of relevant studies, while Sect. 3 describes the methodology used for this study. Section 4 presents the results and discussion, while Sect. 5 concludes.

2 Literature Review

As alluded to, four vital areas of concern in this research are reviewed in this section. The domains examined include various maintenance strategies, spare parts alternatives (3D printed and new), renewal, and their integration with maintenance.

Asset utilization inherently inflicts degradation and leads to unplanned failure. Failure leads to many adverse situations, such as reduced availability, potential secondary failures, and protracted maintenance costs. Various maintenance strategies are employed to mitigate these challenges, including Corrective (CM) and preventive maintenance (PM). PM is planned maintenance based on a prescribed interval dictated by calendar or asset running time. A common PM strategy is the block replacement policy, replacing all the parts after the PM interval. CM is a reactive policy and may include various actions such as repair, replacement, and adjustment, as defined in [1]. An inherent gap in research, as alluded to by [10], is the use of either CM or PM separately despite their simultaneous use in real life, which may lead to suboptimal maintenance. However, as reviewed in the next section, a critical CM and PM action retains replacement, which could be using new parts and other alternatives.

Replacement using new parts is a common spare parts strategy utilized in corrective and preventive maintenance, offering renewed asset reliability. Recently, Additive manufacturing has provided an alternative for new spare parts replacement, especially for remotely located assets. Additive manufacturing is the formal name for what was initially known as rapid prototyping and is also commonly referred to as 3D printing [11]. 3D printing offers a potential solution for spare parts stock-outs between replenishments, quickly producing various parts at low set-up costs by having the production within the plant or nearby [12].

Remanufacturing is an End-of-life extension strategy where used parts are renewed and offer immense benefits like extending the life of an asset by facilitating reuse, restoring a used part to as good as new condition, reducing cost compared to new products, reducing repair time and part supply lead time [3]. Additive manufacturing has also been identified as an interesting option for self-repair by consumers [13]. Various repairing solutions utilized include Laser Metal Deposition and Direct Metal Deposition, among others. However, while exploiting the remanufacturing option for the parts renewal, several limitations must be mitigated, such as the parts return process and the probability of manufacturability of the returned parts, making the process very stochastic. Moreover, as suggested by [3], the remanufacturing decision is sometimes not the first, creating uncertainty in optimal utilization. Modelling generic parts remanufacturing is problematic because it may lean towards being case-specific. Despite several works utilizing remanufacturing as a renewal strategy for degraded parts (e.g., [3, 14]), investigations have yet to be performed integrating 3D printed, remanufactured and new spare parts replacement simultaneously in asset maintenance.

In asset management through maintenance, using spares within the maintenance strategies increases the importance of joint spares and maintenance optimization.

Research that integrates maintenance and alternative spare parts have been done by various authors, such as addressing cement plants [15], marine engines/power plant [16], geothermal drilling rigs [17] and others. However, research in this area has not explicitly considered integrating various maintenance strategies (CM and PM) with alternative parts strategies, in this case, new parts, 3D parts and remanufactured parts simultaneously, also picked as a gap by [3], an aspect this research seeks to address.

Two important themes emerge from the studies discussed so far: Firstly, while addressing maintenance, CM entails various interventions such as repair, replacement, and reuse [1, 15]. However, previously published studies have limited use of replace and repair, where the remaining useful life is renewed to 100% and reduced to zero based on replacement and repair. Much of the potential of the CM strategy remains to be explored where other interventions would not cause significant age reduction. To the author's knowledge, no works have been published so far that consider the various CM actions explicitly and subsumes various spare parts replacement alternatives. Secondly, while some research has been conducted on using 3D printed and remanufactured parts in maintenance, no studies have been found that integrate the three spare parts replacement alternatives (New, 3D printed and Remanufactured) simultaneously with various explicit maintenance (CM and PM) strategies. This has not been previously investigated in the literature; hence, this research seeks to explore using the simulation process, as intimated in the next section.

3 Methodology

This section reviews the simulation-based model development and dynamics and the evaluation and interpretation adopted by this research. A case study using a Turbocharger of a medium-speed engine is utilized. The notations in Table 1 will be used in this research.

Table 1 Notations utilized in the study

i	Number of maintenance actions	I	Turbocharger running hours
M_i	Maintenance strategies	A_o	Operational availability (%)
e_i	Age renewal factor	T_m	Total maintenance time (hrs.)
τ	Preventive maintenance interval	T_{r_i}	Recovery/repair time (hrs.)
η_i	Reliance factor/index	T_l	Sourcing lead time (hrs.)
FS_i	Hazard rate/failure severity	f_{new}	Fil-rate for new parts
ρ_{3D}	3D parts utilization probability	f_{rmf}	Fil-rate for remanufactured parts
$T_{l_{3D}}$	Sourcing lead-time for 3D parts	$T_{l_{new}}$	Sourcing lead-time for new parts

3.1 Simulation Model

The simulation model mimics the failure generation and intervention for components of the turbocharger, as illustrated in Fig. 1. The methodology is similar to [18], but the current one, with remanufacturing as a CM action, we consider three part replacement alternatives (new, 3D and remanufactured) proposed here.

The maintenance actions M_i include CM actions modelled, replacing (M_1), remanufacturing (M_2), repair (M_3), reuse (M_4), in addition to PM (M_5) employing new spare replacement as block replacement policy (BRP). To model the maintenance strategy frequency of usage, the reliance factor $\eta_{i=1,2,3,4}$ is introduced, which indicates the probability usage of the specific M_i during CM in percentage.

While the turbocharger is running, preventive maintenance, in this case, replacement of all components, is done at the turbocharger's scheduled τ running hours (PM interval). While running, random unplanned failures are addressed using corrective maintenance, including several maintenance interventions. The first CM strategy is

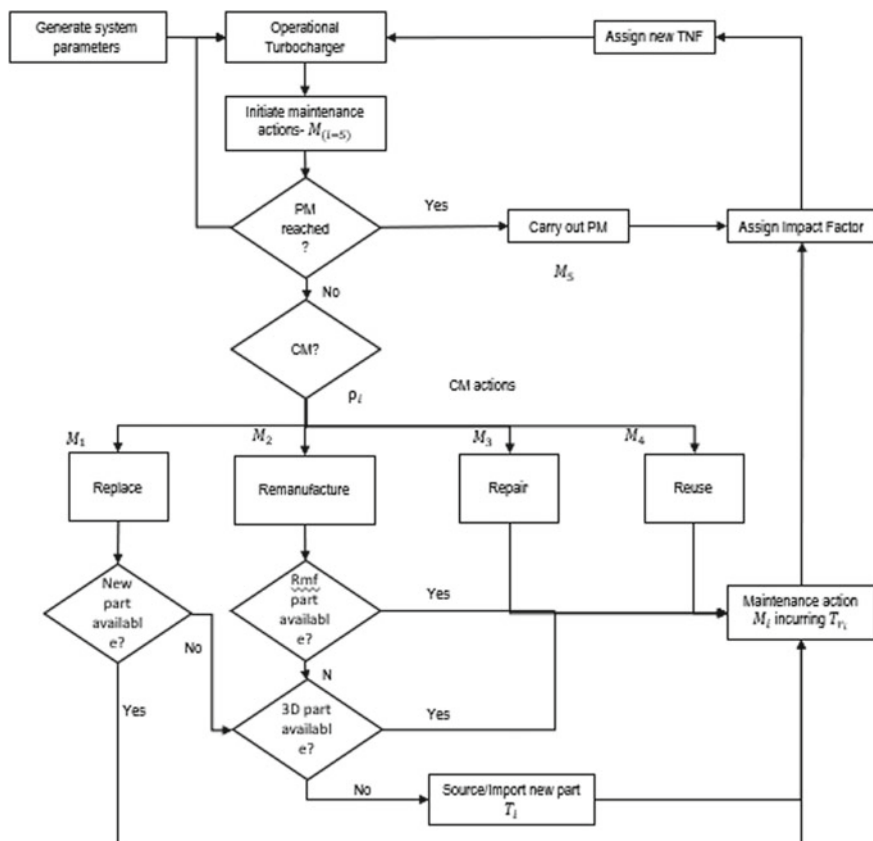


Fig. 1 Conceptual representation of the simulation model

the replacement (M_1), of failed components whose reliance factor is η_1 and MTTR is T_{r_1} . The replacement options include new parts whose fill rate f_{new} is used, while 3D-printed parts follow the utilization ρ_{3D} and lead time ($T_{l_{3D}}$), in the event new parts are unavailable. The last option in the replacement is the sourcing (local or import) of the unavailable parts following a unique lead time ($T_{l_{new}}$).

The second CM strategy, the Remanufacturing strategy (M_2), whose reliance factor is η_2 and MTTR is T_{r_2} , is also employed where the cores of the components are availed earlier, and the OEM-R or an agent can restore components and avail renewed parts with some warranty. The failed part is replaced using a remanufactured part following the fill rate f_{rmf} . If unavailable, 3D printing is done following the utilization probability (ρ_{3D}) and lastly, sourcing the remanufactured part from OEM-R with a lead time $T_{l_{rmf}}$. In this study, it is assumed that the remanufacturing is done after failure occurrence. The third CM strategy is to repair (M_3) whose reliance factor is η_3 and incurs a delay of MTTR T_{r_3} . Lastly is the reuse strategy (M_4) with an MTTR of T_{r_4} and reliance factor of η_4 .

The effective age renewal factor or the impact of the respective recovery/maintenance strategy on a component's remaining useful life, the use of a hazard rate following a Semi Markov Decision Process follows as described in [18].

3.2 Evaluation and Interpretation

This study's critical performance measurements include the turbocharger's operational availability, A_o and the total maintenance time T_m . A sensitivity analysis is performed to ascertain the impact of reliance on replacement and remanufacture strategies and other parameters separately. Additionally, ANOVA is used to derive the significant parameters (main and interaction effects) influencing performance for decision support. During the analysis, the indicated variables will be varied as follows: τ (6,000–12,000 h.), replace reliance η_1 (20–50%), remanufacturing reliance η_2 (10–50%), repair reliance η_3 (5–30%), fill rate for new parts f_{new} (40–100%), fill rate for remanufactured parts f_{rmf} (40–100%) and 3D parts utilization ρ_{3D} (10–50%).

4 Results and Discussion

4.1 Modelling, Verification, and Validation

Model Parameters

We model seven ($n = 7$) critical components in the Turbocharger with respective MTBF derived from data as per [3]. They included the turbine rotor, Turbine blade, nozzle rings, compressor wheel, bearings, lube oil pipe, gasket, and others. τ , 9,000 h;

$\epsilon_1, 90\%$; $\epsilon_2, 95\%$; $\epsilon_3, 65.6\%$; $\epsilon_4, 40.5\%$; $\epsilon_5, 95\%$; $\eta_1, 40\%$; $\eta_2, 30\%$; $\eta_3, 19\%$; $\eta_4, 11\%$. Additional parameters included sourcing lead time T_l , repair/recovery time T_{r_i} for each maintenance strategy.

Modelling and Simulation Results

The performance measures turbocharger availability A_o and the total maintenance time T_m are defined by Eqs. (1) and (2) respectively as follows:

$$A_o = \frac{I}{I + T_m} \quad (1)$$

$$T_m = \sum_{k=1}^n T_{r_k} + \sum_{k=1}^n T_{l_k} \quad (2)$$

The replication length of 105,120 h depicting 12 years of operation was used, while a warm-up period of 60,000 h was employed. To ensure the steady state of the model, 125 replications were established using the halfwidth for the T_m .

Based on the simulation model and the parameters indicated in Sect. 4.1, the Turbocharger availability of 97.27% and the Maintenance time of 2,872.7 h were measured and were within $\pm 10\%$ of the empirically measured performance.

4.2 Sensitivity Analysis of Factors

From the results illustrated in Fig. 2, varying τ shows an increase in T_m while the availability A_o decreases marginally. This infers that the turbocharger experiences increased failures, which can be attributed to the extended time of running for the turbocharger before the planned stoppage for PM. This implies more CM activities which are time intensive are employed, hence the reduction of A_o and increase of T_m . The non-linear characteristics of the T_m the curve indicates potentially an external factor (s) interacting with τ . However, while considering optimal τ , the interactions with other factors must be investigated and considered, as will be investigated in Sect. 4.3. It is worth noting that after extensive sensitivity analysis, τ and the other parameters marginally influence A_o in this case study; hence, based on the preceding, we primarily use the maintenance time T_m performance measure in the following sections.

As shown in Fig. 3, the change or increase in the respective fill rates, which generally infers a high availability of the individual parts, reduces the maintenance time. The observed decrease in T_m , could be attributed to the reduced frequencies of incurring spare parts sourcing lead times when either the new or remanufactured parts are available for replacement. When considering plants near the parts sources, these results may underestimate the role of spare parts sourcing lead times. These actual findings relate to remotely located plants and hence may require to be interpreted

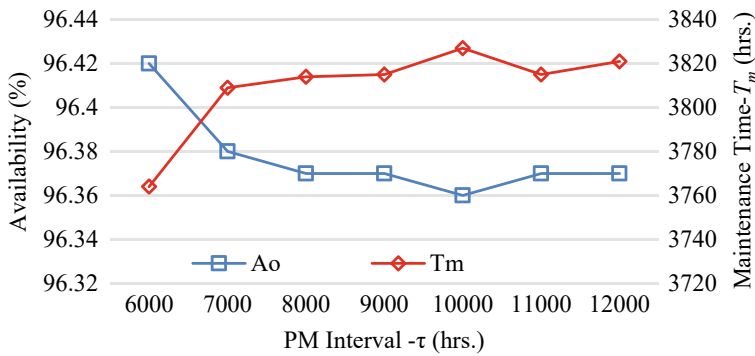


Fig. 2 Variation of the PM interval

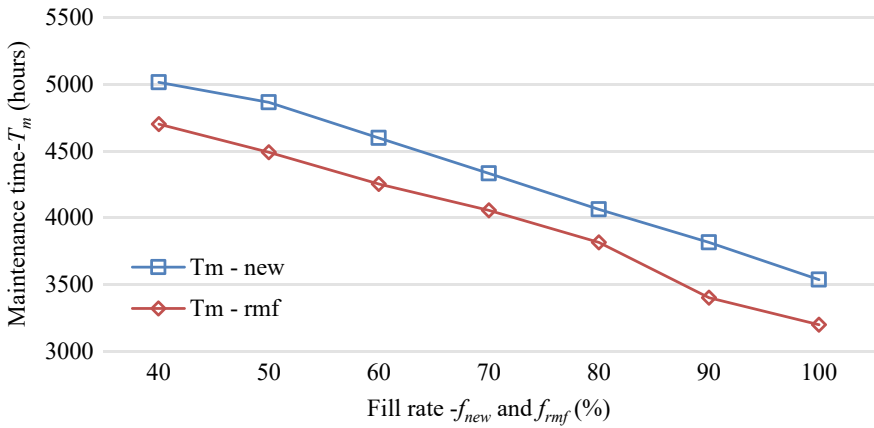


Fig. 3 Variation of the fill rates for new and remanufactured parts

with caution while considering generalization of the same. However, it is essential to note that, on average, the T_m is significantly lower for the remanufactured parts compared to new parts.

As illustrated in Fig. 4, the increase in the spare parts utilization of the 3D, remanufactured and new parts in the replacement action shows a reduction in the T_m . The use of 3D parts indicates a significant drop, followed by the new and remanufactured parts. However, the new and remanufactured parts seem to converge at higher utilization, in this case, 50%. The use of 3D parts shows a significant reduction of T_m , which could be attributed to the localized production of the parts, hence reduced sourcing lead times, ultimately leading to a reduction of T_m . It is worth noting that at higher utilization rates, remanufactured parts will cause a lower T_m than new parts, however, while considering this option, the part core availability and remanufacturing decision-making must be robust and well-articulated.

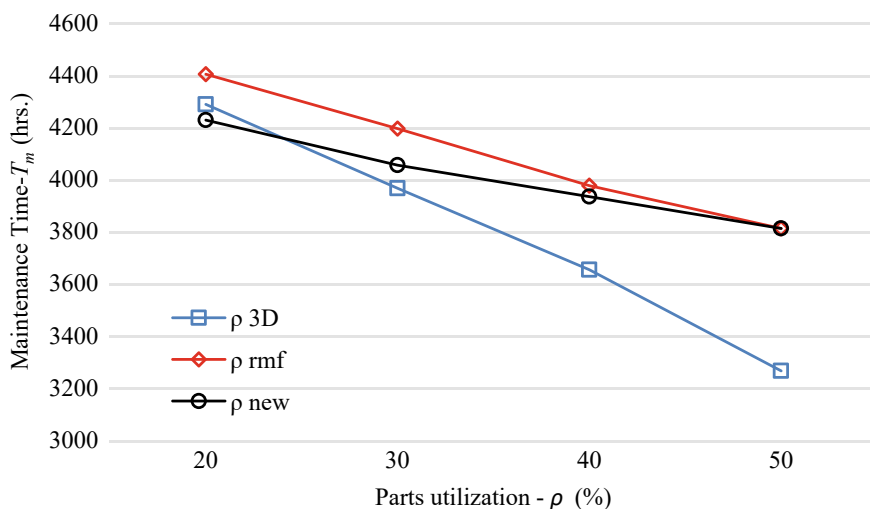


Fig. 4 Variation of the new, 3D and remanufactured parts utilization

From Fig. 5, the increase in replace η_1 and remanufacturing η_2 reliance gradually increases the T_m . However, the increased utilization of η_2 shows a marginally higher T_m compared to η_1 . These results support previous research into this brain area, which links the increase in replacement and remanufacturing utilization and maintenance time. The increased utilization of replacement increased the maintenance time due to the increased usage of time-intensive replacement activities, such as the need to disassemble subsystems to extract and replace the parts. This is in addition to the possible lead times for parts sourcing and the replacement time. The marginal difference between the replacement and remanufacturing is attributed to the additional expected activities in sourcing lead times where, in some cases, parts are returned, and remanufacturing processes like laser deposition are undertaken before the part is used again, as also agreed by [16]. Moreover, some remanufacturing processes for repairing the failed parts with reduced performance, which are more time intensive, can be exploited.

These sensitivity results have significant implications for practitioners, especially where assets are ageing and the plants are remotely located. Despite the replacement η_1 and remanufacturing η_2 reliance, causing an increase of T_m , they inherently allude to significantly influencing asset performance. While combining with the results based on the increased new, 3D and remanufactured parts utilization (see Fig. 3), these findings suggest that an optimal combination and balance of these variables is necessary to improve the asset performance.

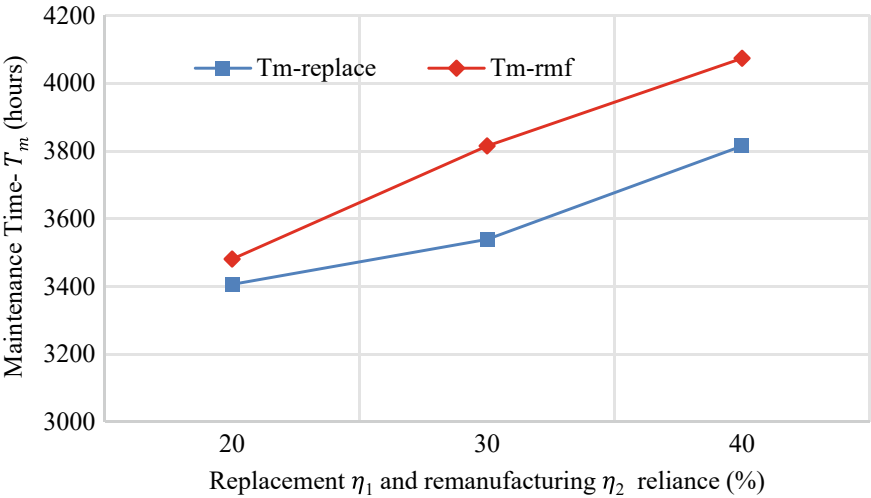


Fig. 5 Variation of the replace η_1 and remanufacturing η_2 reliance

4.3 Main and Interaction Effects

This section provides a quantitative analysis of the Analysis of Variance results. Table 2 shows the effect sources and the various parameters—the main effects and interaction effects.

From the ANOVA analysis illustrated, the system parameters that have a significant effect on T_m , include η_1 which has the most significant effect size based on the Eta squared; others include η_3 , η_2 and ρ_{3D} . Considering the interaction effects, $\eta_1 * f_{new}$ has the largest effect size among the interactions, with a significant effect on T_m . Other interactions with significant effects include $\eta_3 * f_{new}$, $\eta_1 * f_{rmf}$, and $\eta_1 * \rho_{3D}$.

It is worth noting that the interactions have some significant main effects; for instance, f_{rmf} has an eta squared value of 0.488, while η_1 has 0.932. Considering their interactions, the value drops to 0.632. Likewise, f_{new} has an effect size of 0.44, and the interaction $\eta_1 * f_{new}$ increases in general to retain the highest effect size of 0.951.

One of the most significant findings in the analysis was that τ had no significant effect on T_m . This is an interesting finding, as it is contrary to what we know from previous studies, which have shown τ having a significant effect on maintenance performance measures like T_m .

Table 2 illustrates the direct and interactional effects of the decision variables, where D.f is the degrees of freedom. The presented main and interaction effects contain the significant ones, which means that the variables are statistically significant (P-Value 5%); in relation to the equation, interaction effects indicate the validity of determining a balanced trade-off solution while integrating the decision variables

Effect source	Sum of squares	F ratio		p-value	Partial Eta squared	Significant
τ	0.005	1	0.005	0.946	0	Yes
η_3	2.823	1	403.371	0	0.863	Yes
η_1	6.147	1	878.226	0	0.932	Yes
η_2	2.25	1	321.443	0	0.834	Yes
f_{rmf}	32.311	1	114.218	0	0.488	Yes
f_{new}	28.303	1	100.052	0	0.455	Yes
ρ_{3D}	70.256	1	248.353	0	0.674	Yes
$f_{rmf} * \rho_{3D}$	17.888	1	63.233	0	0.345	Yes
$f_{new} * \rho_{3D}$	12.357	1	43.681	0	0.267	Yes
$\eta_3 * \eta_2$	0.063	1	8.94	0.004	0.123	Yes
$\eta_3 * f_{rmf}$	2.506	1	358.04	0	0.848	Yes
$\eta_3 * f_{new}$	0.155	1	22.103	0	0.257	Yes
$\eta_3 * \rho_{3D}$	0.83	1	118.647	0	0.65	Yes
$\eta_1 * \eta_2$	0.092	1	13.132	0.001	0.17	Yes
$\eta_1 * f_{rmf}$	0.734	1	104.806	0	0.621	Yes
$\eta_1 * f_{new}$	8.773	1	1253.399	0	0.951	Yes
$\eta_1 * \rho_{3D}$	2.13	1	304.253	0	0.826	Yes
$\eta_2 * f_{rmf}$	0.047	1	6.7	0.012	0.095	Yes
$\eta_2 * \rho_{3D}$	0.071	1	10.113	0.002	0.136	Yes
$\eta_1 * f_{new} * \rho_{3D}$	3.554	1	507.834	0	0.888	Yes
$\eta_1 * f_{rmf} * \rho_{3D}$	0.46	1	65.665	0	0.506	Yes
$\eta_3 * f_{rmf} * \rho_{3D}$	1.242	1	177.489	0	0.735	Yes
$f_{rmf} * f_{new}$	0.427	1	60.958	0	0.488	Yes
$f_{rmf} * \rho_{3D}$	17.888	1	2555.667	0	0.976	Yes
$f_{new} * \rho_{3D}$	12.357	1	1765.435	0	0.965	Yes
$\eta_3 * \eta_1 * \eta_2$	0.019	1	2.682	0.106	0.04	Yes
$\eta_3 * \eta_1 * f_{rmf}$	0.181	1	25.824	0	0.287	Yes
$\eta_3 * \eta_1 * f_{new}$	0.058	1	8.319	0.005	0.115	Yes
$\eta_3 * \eta_1 * \rho_{3D}$	0.187	1	26.691	0	0.294	Yes
$\eta_3 * \eta_2 * f_{rmf}$	0.042	1	6.06	0.017	0.086	Yes

From the short review above, key factors that emerge include f_{new} , f_{rmf} , ρ_{3D} , η_1 and η_3 . Taken together, these results suggest that the CM actions related to the maintenance actions (η_1 and η_3) and spare parts replacement options (f_{new} , f_{rmf} and ρ_{3D}) form factors that affect the system performance significantly. These results provide some tentative initial evidence that the integrated use of 3D parts, new parts, and remanufactured parts provides a significant performance improvement in the system.

The present results are significant in at least two major respects. Firstly, the analysis successfully identified the significant factors influencing maintenance time and asset performance. Secondly, it offers the maintenance managers insights into the critical factors to improve the system's maintainability and performance.

5 Conclusion

This study was designed to develop a simulation-based model that integrates maintenance strategies (CM and PM) and spare parts strategies while measuring the maintenance time of an asset. In developing the model, parts replacement (one CM intervention) was modelled to simultaneously incorporate new, 3D printed and remanufactured parts. A discrete event simulation model was developed with maintenance time and availability as the performance measures. A case study of a turbocharger was advanced, considering joint PM, explicit CM strategies and Spare parts strategies for the repairable system.

From the main and interaction effect analysis, the fill rates for remanufactured and new parts were demonstrated to have a superior influence on the maintenance time under the parts strategies. Moreover, the utilization of replacement and remanufacturing potentially influenced the maintenance time while considering the CM interventions. Taken together, these findings suggest a role for interaction effects in identifying significant parameters affecting asset performance. This analysis leads to some valuable conclusions, the most important of which is the observation that it is critical to consider interactions of various parameters for robust and optimal decision support. The study findings have significant implications for understanding the parameters requiring further evaluation for improved asset performance. Moreover, the simulation-based experiments and ANOVA analysis on turbocharger maintenance data verify the validity and robustness of the developed technique.

This research was limited to including only the CM and PM strategies; however, it lays the groundwork for future studies into other maintenance strategies with their possible interactions towards an in-depth optimization model. On the other hand, this work was limited to remanufacturing by OEMS. Further studies could examine the effect of localized remanufacturing at the user's plant. To develop a complete picture of integrating the alternative replacement options, additional studies will be needed that consider the explicit modelling of the actual process dynamics. Moreover, an optimization exercise considering the factors in minimizing the maintenance time would offer more robust decision support.

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