algorithms

Review

Unlocking the Potential of Remanufacturing Through Machine Learning and Data-Driven Models—A Survey

Yong Han Kim [1], Wei Ye [2], Ritbik Kumar [1], Finn Bail [3], Julia Dvorak [3], Yanchao Tan [2], Marvin Carl May [3], Qing Chang [4], Ragu Athinarayanan [2], Gisela Lanza [3], John W. Sutherland [1], Xingyu Li [2,*] and Chandra Nath [1]

[1] Environmental and Ecological Engineering, Purdue University, 500 Central Dr, West Lafayette, IN 47907, USA
[2] School of Engineering Technology, Purdue University, 401 N. Grant St., West Lafayette, IN 47907, USA
[3] wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstrasse 12, 76131 Karlsruhe, Germany
[4] Department of Mechanical and Aerospace Engineering, University of Virginia, Charlottesville, VA 22903, USA
* Correspondence: li4558@purdue.edu

Abstract: As a key strategy for achieving a circular economy, remanufacturing involves bringing end-of-use (EoU) products or cores back to a 'like new' condition, providing more affordable and sustainable alternatives to new products. Despite the potential for substantial resources and energy savings, the industry faces operational challenges. These challenges arise from uncertainties surrounding core quality and functionality, return times, process variation required to meet product specifications, and the end-of-use (EoU) product values, as well as their new life expectancy after extended use as a 'market product'. While remanufacturing holds immense promise, its full potential can only be realized through concerted efforts towards resolving the inherent complexities and obstacles that impede its operations. Machine learning (ML) and data-driven models emerge as transformative tools to mitigate numerous challenges encountered by manufacturing industry. Recently, the integration of cutting-edge technologies, such as sensor-based product data acquisition and storage, data analytics, machine health management, artificial intelligence (AI)-driven scheduling, and human–robot collaboration (HRC), in remanufacturing procedures has received significant attention from remanufacturers and the circular economy community. These advanced computational technologies help remanufacturers to implement flexible operation scheduling, enhance quality control, and streamline workflows for EoU products. This study embarks on a comprehensive review and in-depth analysis of state-of-the-art algorithms across various facets of remanufacturing processes and operations. Additionally, it identifies key challenges to advancing remanufacturing practices through data-driven and ML methods and uncovers research opportunities in synergy with smart manufacturing techniques. The study aims to offer guidelines for stakeholders and to reinforce the industry's pivotal role in circular economy initiatives.

Keywords: remanufacturing; circular economy; machine learning; data-driven models; sustainability

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1. Introduction

Remanufacturing is one of the key elements in a circular economy, aiming to restore full or partial value of end-of-use (EoU) products to a 'like new' or refurbished condition through processes such as disassembly, cleaning, repair, component replacement, and reassembly [1,2]. As depicted in Figure 1, through extending the life cycles of products by restoring their values to a near-new condition and keeping the resources in a closed loop as long as possible, remanufacturing conserves valuable resources and reduces the environmental footprint associated with the extraction, processing, and transportation of raw materials for creating brand new products, thereby enhancing sustainability [3,4]. The benefits of remanufacturing are substantial, in terms of resource preservation [5,6], reduced energy intensity [7], lower environmental impact [8], and notable economic gains [9], owing to significant reduction in the use of new materials, water, and other energy sources required for traditional manufacturing processes [10–13].

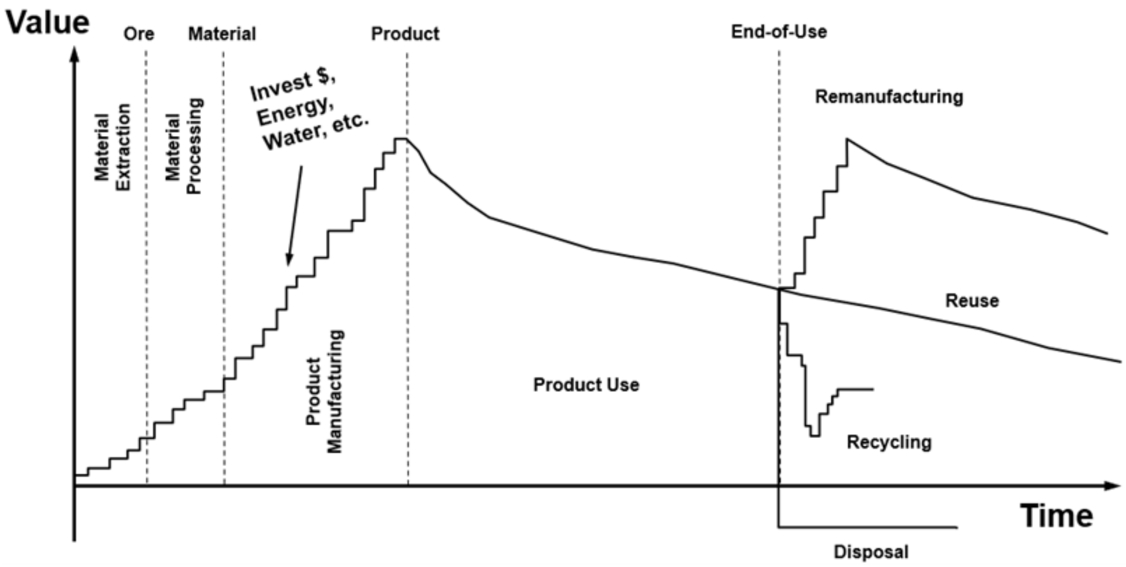

Figure 1. Value recovery over time in a product's life cycle (adapted from [14]).

Among several strategic decisions, in terms of reuse, remanufacturing, recycling, or disposal, as shown in Figure 1, remanufacturing is crucial for enhancing manufacturing sustainability, preserving the value of products, and fostering techno-economic benefits. However, the conceptualization and implementation of remanufacturing involves several significant challenges. First, the inherent uncertainty in product condition and mechanical functionality arises from the duration and environment of the product's use, as well as the consumer's independent decision to return it. Guide et al. highlighted that uncertainties regarding the timing, quantity, and condition of materials recovered from cores are critical factors complicating decision-making in remanufacturing [15]. Factors such as component condition, disassembly sequence, and market values are crucial in trading off between sustainability and profitability [16]. Additionally, the remanufacturing process necessitates an effective reverse logistics system to facilitate the acquisition of cores from the market. The complexity of adapting to customer behaviors and incentives for participating in reverse logistics further complicates the coordination of various stages. This necessitates enhanced data visibility in areas such as product quality, material flow, energy flow, shopfloor operations, and inventory management [17,18]. Therefore, efficient tracking of products and usage information across the life cycle are vital for optimizing remanufacturing efforts [12,19].

The heterogeneous quality conditions of returned products require customized production and planning strategies during remanufacturing and associated procedures. Variability in core conditions leads to fluctuating processing times, different reconditioning paths, variable inventory control and resource allocation, and complex re-entrant routings [20,21], creating a dynamic and challenging operational environment [20]. Accordingly, these variations demand extensive manual operation [22], involving core assessment, operation sequencing, and selection of disassembly and reconditioning techniques. The complexity of planning the remanufacturing process requires a deep knowledge of product design, failure modes, and production capabilities [23]. A study on the remanufacturing procedure of EoU returned products indicated that grading cores into different quality classes by involving humans can enhance profitability by only up to 4% [24]. To address the above-mentioned challenges, thereby improving remanufacturing efficiency and overall plant profits, recent advancements have introduced automation and HRC technologies that facilitate the adaptation of processes to varying core conditions. This includes incorporating advanced in-line/in situ inspection technologies, collaborative robots, decision support systems, and automated disassembly planning tools [1].

The advent of Industry 4.0 and advanced computational methods, such as ML and data-driven analysis, offer promising solutions to address the challenges faced by the remanufacturing industry [25]. Technologies such as the Industrial Internet of Things (IIoT) [26], Digital Twins [27], Cobot [28], Virtual Reality (VR), and Augmented Reality (AR) [29,30] could help fast and accurate data acquisition, real-time data access, and support improving efficiency during remanufacturing activities in different ways [31]. Data-driven and ML methods are poised to improve remanufacturing by enabling more precise prediction and classification of product conditions [32], thereby improving quality control and waste management [21]. Additionally, these advanced techniques can optimize inventory management and operational scheduling [1,33], leading to further cost reductions, improved operational efficiency, and resource utilization. Despite the potential alignment, research on developing ML and data-driven methods for remanufacturing systems is still in its early stages [34], indicating that a comprehensive baseline and critical discussion of existing research opportunities and gaps is critically required.

This review study systematically explores the synergistic impacts of advanced computational technologies on remanufacturing activities. Our approach makes a three-fold contribution to the existing research as follows: (i) a systematic review of the existing literature on remanufacturing to understand current trends, major topics, and potential synergies with advanced computational methods (refer to Section 2); (ii) the development of a conceptual framework that integrates data-driven and ML methods into remanufacturing processes, advancing theoretical understanding of their interactions and impacts (Section 3); and (iii) the identification of research gaps and opportunities related to the implementation of smart technologies and advanced computing methods in remanufacturing procedure in industry (Section 4). Section 5 presents our findings and outlooks in the context of smart manufacturing, followed by concluding remarks in Section 6.

2. Remanufacturing Literature Topic Analysis

A topic model is utilized to understand the underlying topics in remanufacturing related research. This approach enables us to understand the current state, underlying topics, and trend of remanufacturing-related research. By mapping out the existing knowledge base, we can better assess how advanced computational methods intersect with remanufacturing practices and pinpoint areas for further investigation and development. To ensure a comprehensive and technically relevant literature review, we deliberately focused on high-impact journals and peer-reviewed conference papers sourced from the *Web of Science*, prioritizing sources that contribute to the understanding and development of remanufacturing systems. Our query, executed on 10 June 2024, utilized the keyword *"remanufactur*"* (Topic), resulting in a collection of approximately 6000 articles related to remanufacturing.

Figure 2 illustrates the upward trend in remanufacturing-related publications over the past 50 years, with a notably steeper increase since 2008. This surge indicates a significant rise in scholarly interest and activity in the remanufacturing field, likely driven by advancements in smart manufacturing technologies and an increasing emphasis on manufacturing sustainability and global decarbonization goals. Since 2014, propelled by advancements in information and communication technologies, there has been a clear, sustained increase in the application of data-driven and AI/ML methods in remanufacturing research, with a growth rate exceeding 30% annually, underscoring the field's growing attention to and methodological alignment in tackling remanufacturing challenges.

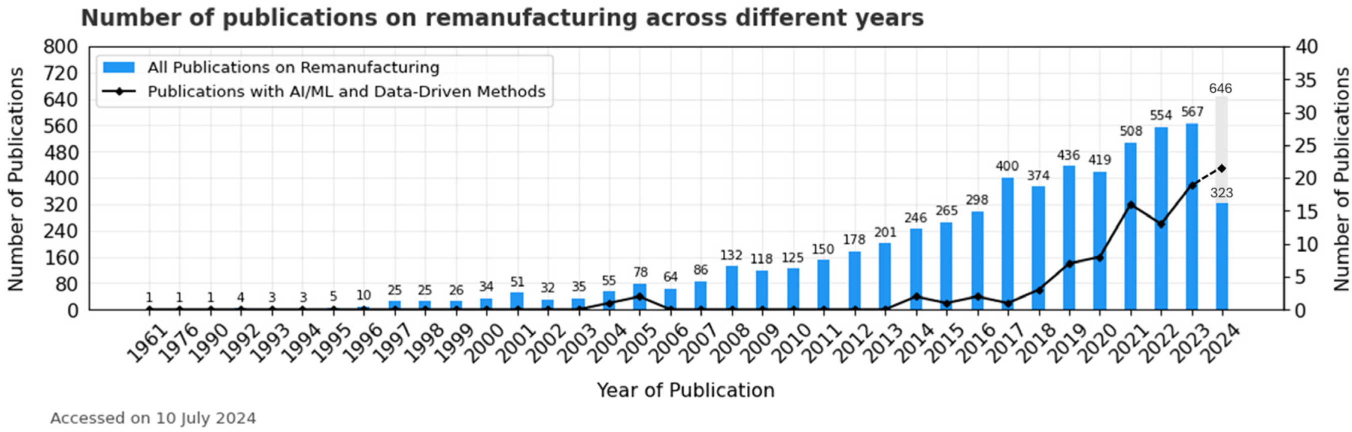

Figure 2. Annual publication trends in remanufacturing (blue bars) and in AI/ML and data-driven methods applied to remanufacturing (black solid line) over the past 60 years (as of July 2024). Projected 2024 values for remanufacturing publications and AI/ML data-driven publications are shown by grey bars and a dashed line, respectively. Source: Web of Science—Remanufacturing—https://www.webofscience.com/wos/woscc/basic-research accessed on 10 July 2024.

To uncover the latent topics and their distributions within the collected remanufacturing literature, we employed the *Latent Dirichlet Allocation* model [35], a widely recognized technique for topic modeling, to the abstracts of all collected articles. Given the limited body of literature specifically addressing AI/ML and data-driven methods in remanufacturing, the topic model may have limitations in identifying themes within this smaller subset. Our analysis seeks to clarify the dominating topics of remanufacturing-related research and reveal potential avenues for understanding the synergistic effects of integrating ML and data-driven methods with remanufacturing practices. Table 1 presents the results of the model, which identified nine distinct topics across the collected 6000 articles. Each topic was named based on the most frequently occurring terms in the associated articles to aid in interpreting the thematic content. For instance, 'Topic 0' prominently features words such as *'closed_loop'* and *'closed_loop supply chain'*, leading to the topic name *'Closed-Loop Supply Chain'*.

Table 1. Overview of identified remanufacturing topics based on their frequent keywords.

Index	Topic Names	Frequent Words
0	Closed-Loop Supply Chain	*'closed_loop', 'closed_loop supply chain'*
1	Reverse Logistics	*'reverse', 'logistics'*
2	Carbon Emission	*'carbon', 'emission', 'reduction'*
3	Life Cycle Management	*'life_cycle', 'circular_economy', 'reuse'*
4	Inventory Policy	*'inventory', 'policy', 'return'*
5	Collaborative Business Models	*'retailer', 'third-party', 'manufacturer'*
6	Process Optimization	*'disassembly', 'assembly', 'planning'*
7	Repair Technologies	*'laser', 'cladding', 'coating'*
8	Techno-Economic Assessment	*'economic', 'sustainable', 'company'*

To further analyze the topics and their interrelationships, we used the *t-distributed Stochastic Neighbor Embedding (or t-SNE)*, which is a nonlinear dimensionality reduction technique that can visualize high-dimensional data in a low-dimensional space. Figure 3 presents the topic distributions in a two-dimensional space to help understand the relationships in the data. The x- and y-axes of the plot represent new abstract coordinates derived by the t-SNE algorithm. These 2-dimensional (2D) coordinates are not tied to any specific features or values from the original data. Instead, they are designed to visualize the high-dimensional topic labels in a lower-dimensional space. Each dot in the scatter data represents an article, with the color of the dot indicating the corresponding topic category. The distance between dots reflects the similarity of topics; dots of the same color are typically located in close topic proximity, while the spatial arrangement of different clusters indicates the degree of similarity among various topics.

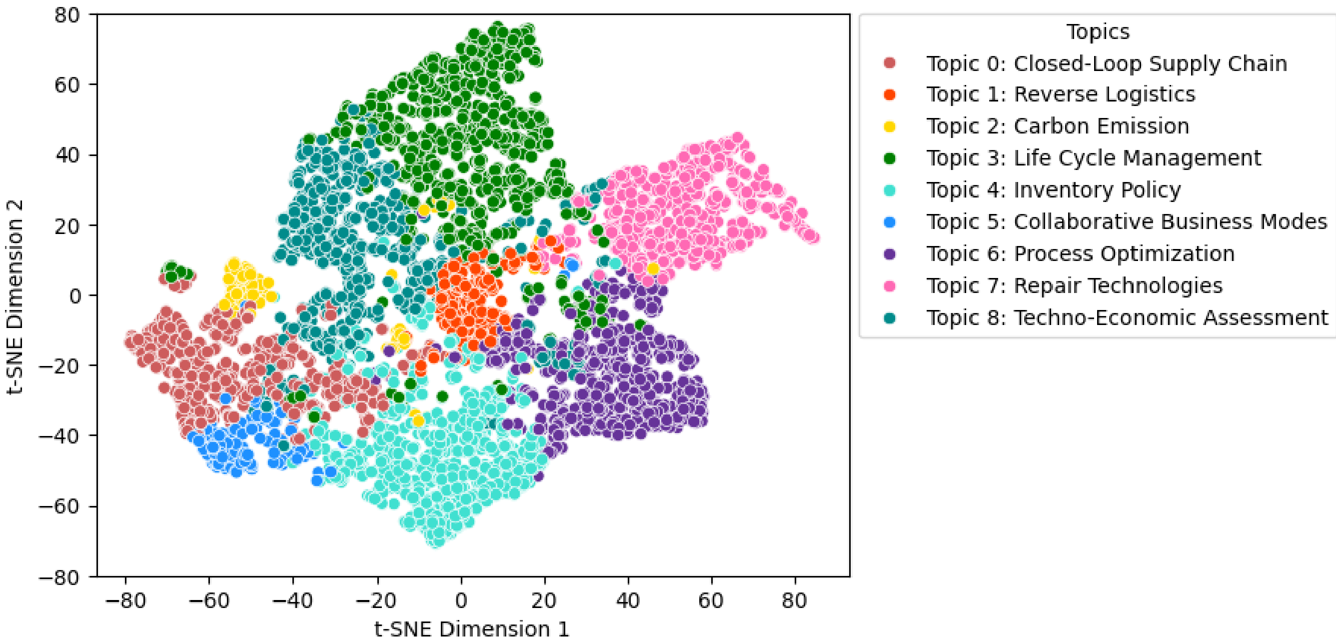

Figure 3. Articles clustered by topics visualized in the 2D space across the collected 6000 articles.

By visualizing the topics and their interrelationships using the *Latent Dirichlet Allocation* model, we identified key themes and areas of focus within the field and pinpointed where advanced computational technologies may have the most impact, particularly in topics such as *closed-loop supply chain*, *reverse logistics*, *carbon emission*, *life cycle management*, *inventory policy* and *process optimization*. Additionally, the identified individual articles' thematic alignments, and how these themes interact and overlap within themselves underscore the potential for collective advancements across various facets of remanufacturing through the application of ML and data-driven methods.

3. ML and Data-Driven Models for Remanufacturing

ML and data-driven models leverage algorithms and statistical techniques to analyze and interpret complex and high-volume data in many fields including manufacturing [36–39]. In remanufacturing, these technologies offer significant potential to enhance various aspects, such as the automated sorting of a wide range of products, improving asset management, facilitating real-time decision-making, and optimizing the entire product life cycle. These technologies can deliver innovative solutions for sequence optimization, quality control, and predictive analysis throughout remanufacturing processes. In this section, we present a detailed summary of key ML and data-driven methods, including explanations of their potential benefits for remanufacturing.

IIoT: By connecting industrial machinery and devices to data collection systems, cloud platforms, and the internet, the Industrial Internet of Things (IIoT) supports extensive data acquisition and real-time analysis across the manufacturing ecosystem [31,40,41]. For remanufacturing, IIoT facilitates fast and accurate asset tracking and inventory management by providing detailed core histories and spare parts availability. Emerging sensing technologies allow accessibility by installing sensors on the inner structure of machines to better understand the machine's operational statuses [42] and support automation by allowing machines to communicate and coordinate with each other [43], resulting in coherent remanufacturing processes.

Traceability: Traceability systems, such as digital product passports (DPP), track the history, location, and status of products throughout their life cycle [44]. For the purpose of remanufacturing, these tools provide detailed histories of cores, ensuring remanufacturers can access all relevant information about previous repairs, modifications, and usage conditions [45]. These data help in assessing the condition of returned EoU products and determining the best remanufacturing approach. The systems also ensure compliance with regulatory standards and build consumer confidence by offering transparency about the origins of materials and processes involved in remanufactured products [46].

ML models: Supervised and unsupervised learning and reinforcement learning (RL) technologies can analyze vast amounts of data to make informed decisions, optimize processes, and predict future outcomes [47,48]. In remanufacturing, these technologies enable predictive analytics to evaluate which parts will need remanufacturing, provide dynamic planning for the timely streamlining of workflows, and support quality assurance to ensure that remanufactured products meet stringent standards [49,50]. AI can also help in designing and facilitating efficient remanufacturing processes by learning from historical data and continuously improving process quality [42] and equipment healthiness [51]. Key ML models applied in remanufacturing include neural networks, deep learning models, and reinforcement learning algorithms as follows: (i) **Neural Networks and Deep Learning Models**, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have found significant applications in remanufacturing. CNNs excel in visual inspection tasks, enabling automated defect detection and quality control in remanufactured products [52]. LSTM networks, with their ability to process sequential data, are particularly useful for predicting equipment health and product life cycles, crucial for optimizing maintenance schedules and remanufacturing timing [53,54]; (ii) **RL models**, including Q-Learning, Deep Q-Network (DQN), and Proximal Policy Optimization (PPO), have emerged as powerful tools for dynamic decision-making in remanufacturing processes. These algorithms can optimize workflows, resource allocation, and adaptive quality control processes, learning from continuous feedback to improve remanufacturing strategies over time [55–57].

Data-Driven and Optimization Models: Data-driven and optimization models utilize quantitative algorithms to enhance decision-making. These models include: (i) **Graph-based models**, such as AND/OR Graphs [58,59] and Petri Nets [60], which provide a framework for modeling complex remanufacturing systems and processes, especially in HRC. These models are particularly effective in optimizing disassembly sequences, modeling production workflows, and task allocation within humans and robots; (ii) **Mathematical Programming Models**, including Convex Optimization [61], Linear Programming (LP) [62] and Nonlinear Integer Programming (NLIP) [63,64], offer robust solutions for complex planning and scheduling problems; (iii) **Meta-Heuristics** are optimization methods designed to generate or select heuristics that provide sufficiently good solutions to complex optimization problems [65,66]. In remanufacturing, meta-heuristics, such as the Genetic Algorithm (GA), Bees Algorithm (BA), and Particle Swarm Optimization (PSO), can be used to solve intricate problems related to scheduling, resource allocation, and process optimization [67]. These techniques are particularly useful when dealing with multiple objectives [68] and dynamic remanufacturing environments [69]; (iv) **Probabilistic Models**, including Monte Carlo simulation [70] and Markov chains [71], play a crucial role in modeling uncertainty and stochastic processes inherent in remanufacturing. These models assist in assessing risks, and optimizing decision-making under uncertainty, which is essential given the variable nature of returned products in remanufacturing.

It is important to highlight advanced manufacturing technologies that can provide additional opportunities that could be synergized with the aforementioned algorithms to further enhance remanufacturing processes. Immersive technologies like VR and AR could enhance remanufacturing by providing real-time, detailed visualization and simulation, thereby improving training, design, and troubleshooting processes. VR simulates complex scenarios, while AR assists in assembly, disassembly, and maintenance activities by overlaying digital information onto the physical world, thus enhancing accuracy and reducing training time [72]. Cobots work alongside humans to increase productivity, precision, and safety by handling automated disassembly, cleaning, and reassembly tasks. Cobots are versatile and can be programmed for various tasks, thereby reducing injury risk and ensuring consistent quality in remanufacturing operations [73].

4. Literature Review

In this section, we aim to gain a comprehensive understanding of the field and identify research gaps and opportunities by providing a literature review on the synergies between data-driven and ML methods in remanufacturing. We systematically sorted the literature by matching identified remanufacturing topics in Table 1 with advanced computational methods, as summarized in Table 2. First, we examined the application and associated impacts of the IIoT on life cycle management and closed-loop supply models, emphasizing how these technologies facilitate data-driven decision-making in support of circular economy initiatives (Topics 0–4 in Figure 2). Next, we discuss the potential of optimization and ML techniques to enhance dynamic scheduling and HRC within remanufacturing processes (Topic 6), enabling optimized decision-making amidst uncertainties. Finally, we present our review work on utilizing ML models to understand and manage the quality of remanufacturing processes and products, addressing Topics 6–7.

Figure 4 provides a comprehensive overview of the interactions between machine learning (ML) and data-driven models within remanufacturing tasks, highlighting their connections to life cycle management, scheduling and planning, quality control, and HRC. These areas are supported by a variety of ML and data-driven models, ranging from neural networks to probabilistic approaches. Each model is associated with specific tasks in remanufacturing research, as identified in our literature review.

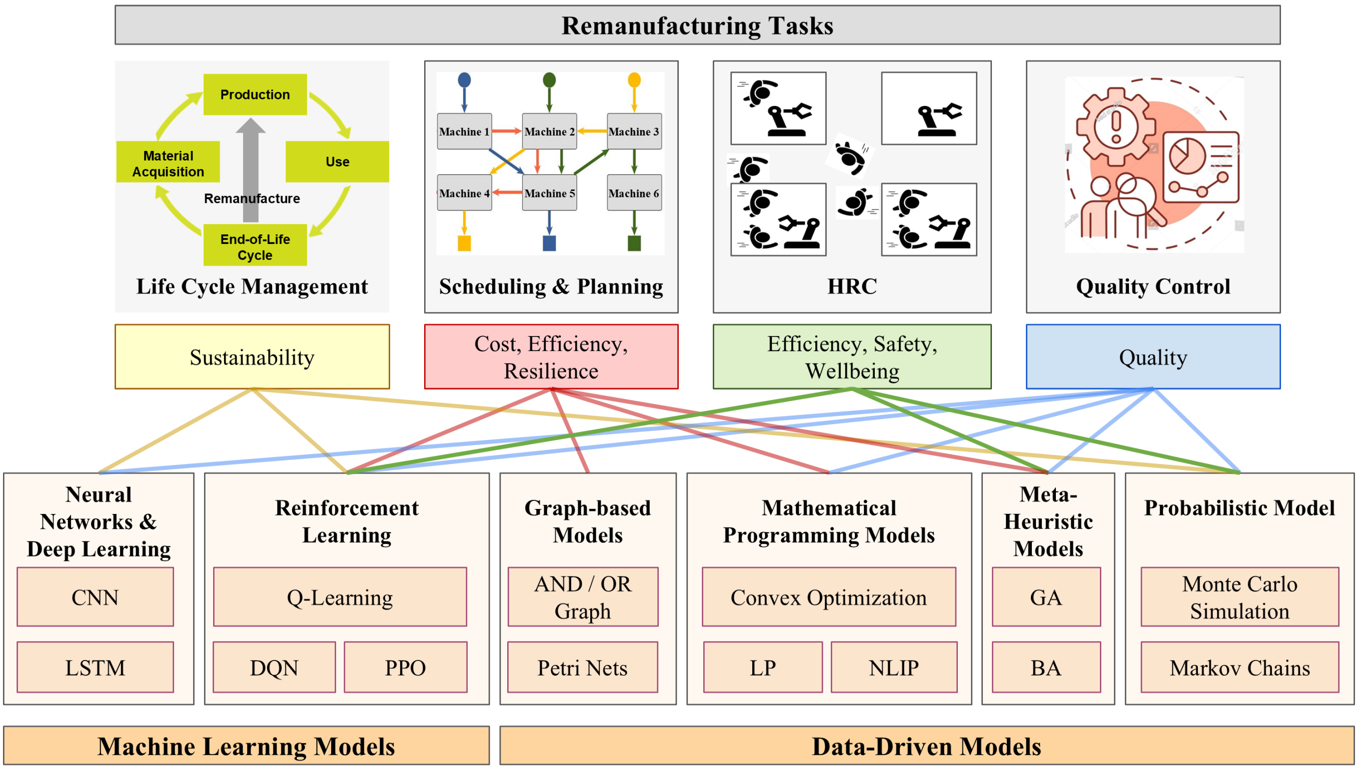

Figure 4. Machine learning and data-driven models and their role in remanufacturing. Abbreviations: CNN—Convolutional Neural Network, LSTM—Long Short-Term Memory, DQN—Deep Q-Network, PPO—Proximal Policy Optimization, LP—Linear Programming, NLIP—Nonlinear Integer Programming, GA—Genetic Algorithms, BA—Bees Algorithm.

Table 2. Applications of machine learning and data-driven models in key remanufacturing topics.

Topics	Applications	Algorithms	Key Findings
Life cycle management	Cylinder heads [44], Energy labeling [46], Aerospace blades [74], E-waste [75], Battery [76,77], Automated vehicle [78], Engine [79]	IIoT [74], Life cycle assessment (LCA) [80], Cobot [77], Digital Twin [78,79], Digital Passport [44–46,75,76]	• Real-time monitoring systems with IIoT and DT enhance the precision, efficiency and success rates of recovering high-value components and materials, thereby contributing to extending product life cycles. • Digital twins and predictive analytics can help forecast EoL scenarios, support proactive maintenance, and ensure that products are effectively remanufactured or recycled.
Reverse logistics	Manufacturers [45], Engine [81], Tactical decisions [82], Solid waste [83], Laptop [84]	Digital passport [45], Digital Twin [81,82], IIoT [81,83,84]	• Digital tools like RFID and cloud-based systems enhance traceability in reverse logistics, minimizing uncertainties in product returns and waste collection. • The integration of advanced technologies supports dynamic management of stochastic demand and material flows, leading to more efficient reverse logistics.
Carbon emission	Food supply chain [85,86], Wind turbine [87]	IIoT [85–87], LCA [80,86], Blockchain [80]	• Integrating LCA with emerging technologies such as IIoT and Blockchain enables accurate real-time monitoring. • IIoT, smart sensors and Blockchain can reduce carbon emissions by optimizing resource utilization, but the energy required for their production and disposal might introduce additional emissions, necessitating a balance in these trade-offs.
Closed-loop supply chain	Manufacturers [45], Food supply chain [85,86], Wind turbine [87], A manufacturing facility [80], Information technology [88], Smartphone [89], Battery [90], Trade-in policy [91]	Digital passport [45], IIoT [85–92], LCA [80,86], Blockchain [88,91]	• Digital integration in the supply chain facilitates better tracking of product returns and efficient materials management, contributing to the overall sustainability of the supply chain. • Successful closed-loop supply chains require improved collaboration among stakeholders, which could be supported by digital platforms that enable data sharing and coordination.
Process optimization	Acquisition strategy [61–64,93–96], Price optimization [97], Process planning [98], Sequence planning [70,99,100], Job shop scheduling [55,101], Carbon footprint [102], System control [56,57,103,104]	Convex Optimization [61], Nonlinear programming [63,64], Linear programming [62], Monte Carlo simulation [70], GA [101], BA [28,100], Deep Q-learning [55,57], PPO [56,103], Root cause analysis [105], Deep belief networks [106]	• Data drive models and ML can help optimize remanufacturing processes through integrating production, planning, and process control mechanisms. • Smart technologies reduce human errors, eliminate individual subjectivity and contribute towards efficient resource utilization.
Repair technology	Process control [107–109], Sorting [105]	RL [32], CNN [105], Transfer learning [106], Gaussian process regression model [107]	• Advanced computational algorithms help devise efficient inspection strategies that play a key part in remanufacturing. • ML assists in continuous improvement and enhances quality assurance through establishing and maintaining product and process key characteristics.
HRC	Assembly [59,60,71,110–112], Quality inspection [58,113], Disassembly [28,70,99,114–121], Remanufacturing [95,100]	AND/OR graphs [58,59], Fuzzification [70], BA [28,99,100], PSO [118], Optimization [115–117,120,122], Transfer learning [121], RNN [111,113], Markov Chains [71], Petri Nets [60], RL [112]	• Balancing of different objectives is essential in HRC • The selection of algorithms varies based on the specific problem types and remanufacturing applications.

4.1. Life Cycle Management

Digital technologies, such as the IIoT, digital twins, and cyber-physical systems, are crucial for implementing data-driven and ML models and for optimizing various facets of the remanufacturing, including process quality control, operational efficiency, LCA, and supply chain management. IIoT techniques facilitate data collection, storage, and analysis, and real-time monitoring, thereby enhancing the visibility and management of the remanufacturing process and the entire life cycle [81]. One study found that integrating machine vision systems and IIoT techniques into aerospace remanufacturing significantly enhances the process by enabling intelligent sensing, real-time data acquisition, and advanced monitoring systems, resulting in higher repair yields, reduced human error, and improved operational safety [74]. Adopting data-driven decision-making in remanufacturing reduces costs, optimizes operations, and enhances quality through real-time insights and predictive analytics [77].

Cyber-physical systems and digital twins create real-time, digital replicas of physical processes, aiming to strengthen synchronization, efficiency, and predictive capabilities across the entire remanufacturing system [123]. A proposed control mechanism based on big data analysis, incorporating cyber-physical systems and digital twin techniques, aims to mitigate uncertainty in remanufacturing using real-time perception and predictive optimization [78]. Moreover, a digital twin model enhanced with a neural network and the Bees Algorithm (BA) for real-time data-driven decisions was presented to optimize remanufacturing planning [79]. Figure 5 presents a proposed conceptual framework to integrate data across the various stages of life cycle management [124].

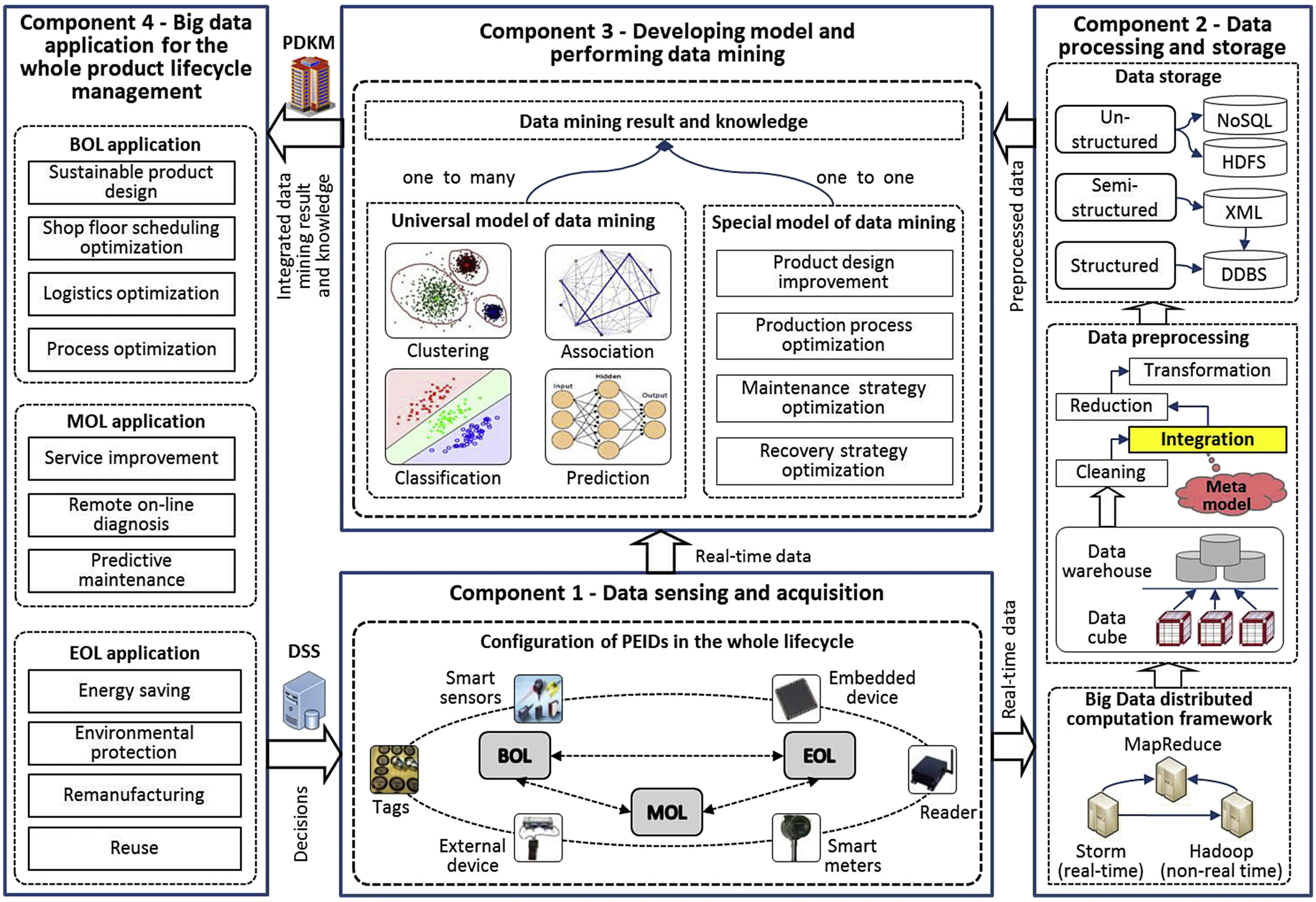

Figure 5. Conceptual framework for integrating big data into product life cycle management (taken from [124]).

The framework includes four major components: data sensing and acquisition, data processing and storage, model development and data mining, and big data application for product life cycle management. The data sensing and acquisition phase gathers information from various life cycle stages through product-embedded devices such as Radio Frequency Identification (RFID) tags and smart sensors, enabling real-time tracking of the status of products, materials and machines. The data processing and storage phase handles the collected data using distributed systems such as Hadoop and Storm, allowing for real-time and non-real-time data analysis and storage. The model development and data mining phase creates models to extract knowledge from big data, including both general models (such as classification, clustering and prediction) and specific models tailored to tasks like enhancing product development and optimizing manufacturing processes. The big data application for product life cycle management phase utilizes the analyzed data to support real-time decision-making, enabling efficient production, logistics and maintenance [124].

Figure 6 illustrates a conceptual model from [125] that integrates IIoT concepts into remanufacturing, establishing a framework for real-time information capture and integration, aiming to facilitate the implementation of data-driven production scheduling on the shop floor [125]. Digital technologies have contributed significantly to LCA methodologies and environmental impact evaluations. LCA is an effective method for measuring the environmental impacts of a system throughout its entire life span [126]. The environmental benefits of smart sensors in reducing food loss were assessed using an LCA model, which highlighted the need to manage potential environmental burdens from sensor manufacturing and disposal for overall sustainability [85]. Zhu et al. introduced a novel four-layer LCA framework integrating IIoT technology to improve real-time data collection and monitoring, demonstrated through a wind turbine case study [87]. Additionally, Zhang et al. developed a new LCA model incorporating blockchain, IIoT, and big data analytics to enhance the efficiency and reliability of LCA, improving data integrity and decision-making [80]. Figure 7 illustrates a multi-level blockchain-based LCA system designed in [80] that connects the manufacturing infrastructures and activities at different stages with a diverse range of applications and users. Moreover, an open-source LCA tool utilizing IIoT to track food quality and assess environmental impacts across multiple stages of the food supply chain was also introduced [86]. Digital technologies have been applied to waste management, playing a critical role in improving product design for remanufacturing. Waste streams of automotive products were analyzed to support product design that facilitates remanufacturing [127] and to determine factors that impede the reuse of parts [128]. Wang et al. introduced WRCloud, a novel service-oriented remanufacturing platform based on cloud manufacturing principles, designed to improve interoperability, intelligence, and adaptability in managing waste electrical and electronic equipment [129].

IIoT is crucial for advancing data acquisition and sharing throughout various closed-loop supply chain stages and remanufacturing processes [130]. AI and blockchain technologies can strengthen supply chain resilience and sustainability by facilitating operations such as just-in-time manufacturing, streamlined automation, and remanufacturing [88]. Additionally, Pan and Miao presented a model for assessing risks in closed-loop supply chains for remanufacturing using neural networks to improve risk assessment accuracy and supply chain management [92]. Yu proposed a novel mathematical model to assist decision-making in reverse logistics for remanufacturing and discussed the impacts of IIoT technology on remanufacturing companies [82]. Innovative approaches in closed-loop supply chain management leverage digital technologies to enhance efficiency and sustainability. For instance, a closed-loop supply chain model utilizing IIoT data has been proposed to optimize the life cycle of products, focusing on EoL recovery processes, including cost and demand for remanufacturing [89]. Similarly, Tavana et al. designed a circular supply chain network for handling electric vehicle lithium-ion batteries, leveraging IIoT and big data technologies to address uncertainties and enhance overall management efficiency [90]. The integration of IIoT with a kanban system has enabled real-time monitoring and dynamic scheduling in reverse logistics, improving waste collection and recycling processes [83]. Additionally, Tozanlı et al. investigated trade-in strategies within closed-loop supply chains, optimizing disassembly decisions through simulations integrated with IIoT and blockchain technologies [91]. The use of embedded IIoT devices to evaluate product designs for EoL recovery helps determine the most effective designs for remanufacturing, increasing profitability and reducing waste [84].

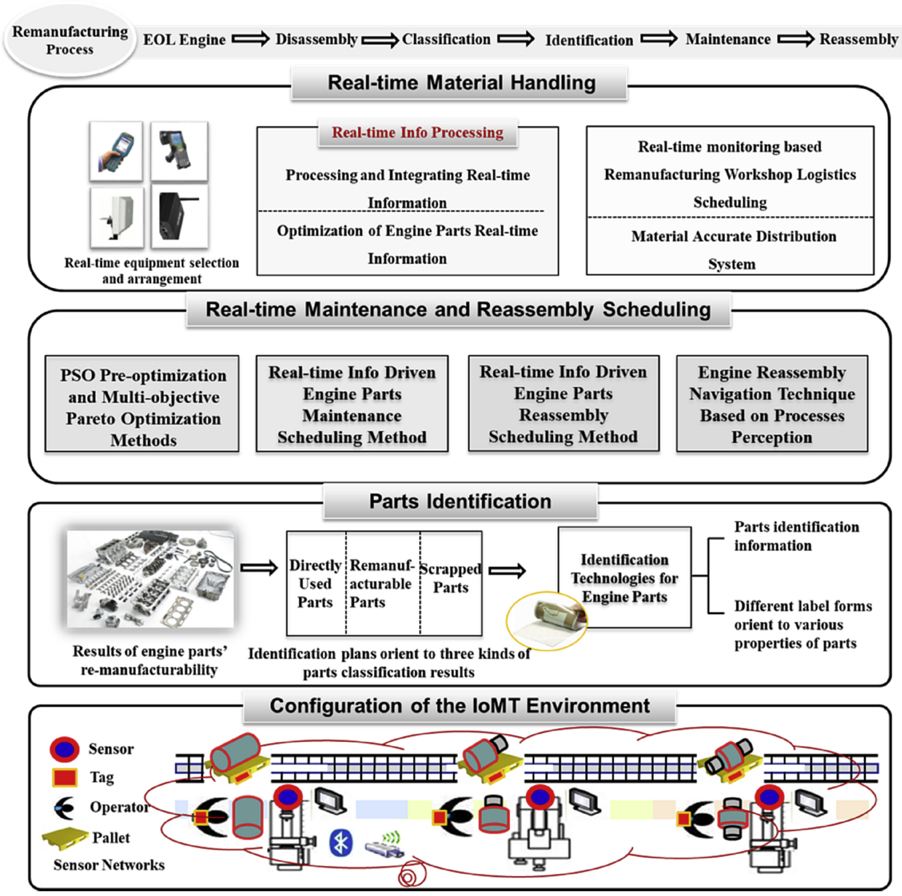

Figure 6. IIoT-integrated scheduling model for engine remanufacturing (adopted from [125]).

The acquisition and collection of cores depend not only on customers and usage history as identical products can be different in quality [131]. A DPP can enhance the acquisition and collection of cores by providing detailed, real-time data on product history and condition, which improves the predictability of recovery processes and differentiates between varying quality levels [132]. Plociennik et al. introduced a Digital Life Cycle Passport, utilizing a cloud-based platform and the Asset Administration Shell, which enabled comprehensive data sharing across the product life cycle, as described in Figure 8. This was exemplified by an e-waste sorting case study that showcased its potential to automate and optimize sorting decisions [75]. Adisorn et al. also explored the role of DPPs as a policy tool for supporting a circular economy, emphasizing their capacity to provide critical product-related information to stakeholders throughout the product life cycle [46]. Additionally, Berger et al. identified key information requirements for Digital Battery Passports, including specifications, diagnostics, and maintenance data, which were essential for managing and making decisions throughout the electric vehicle battery life cycle [76]. Jensen et al. further detailed the data needs for DPPs to enhance circular supply chain management, identifying seven crucial data clusters through a mechatronics case study [45]. Szaller et al. investigated the impact of DPPs on information sharing in remanufacturing processes, demonstrating that increased information availability through DPPs reduced production uncertainties, lowered non-productive time, and improved the remanufacturing ratio [44].

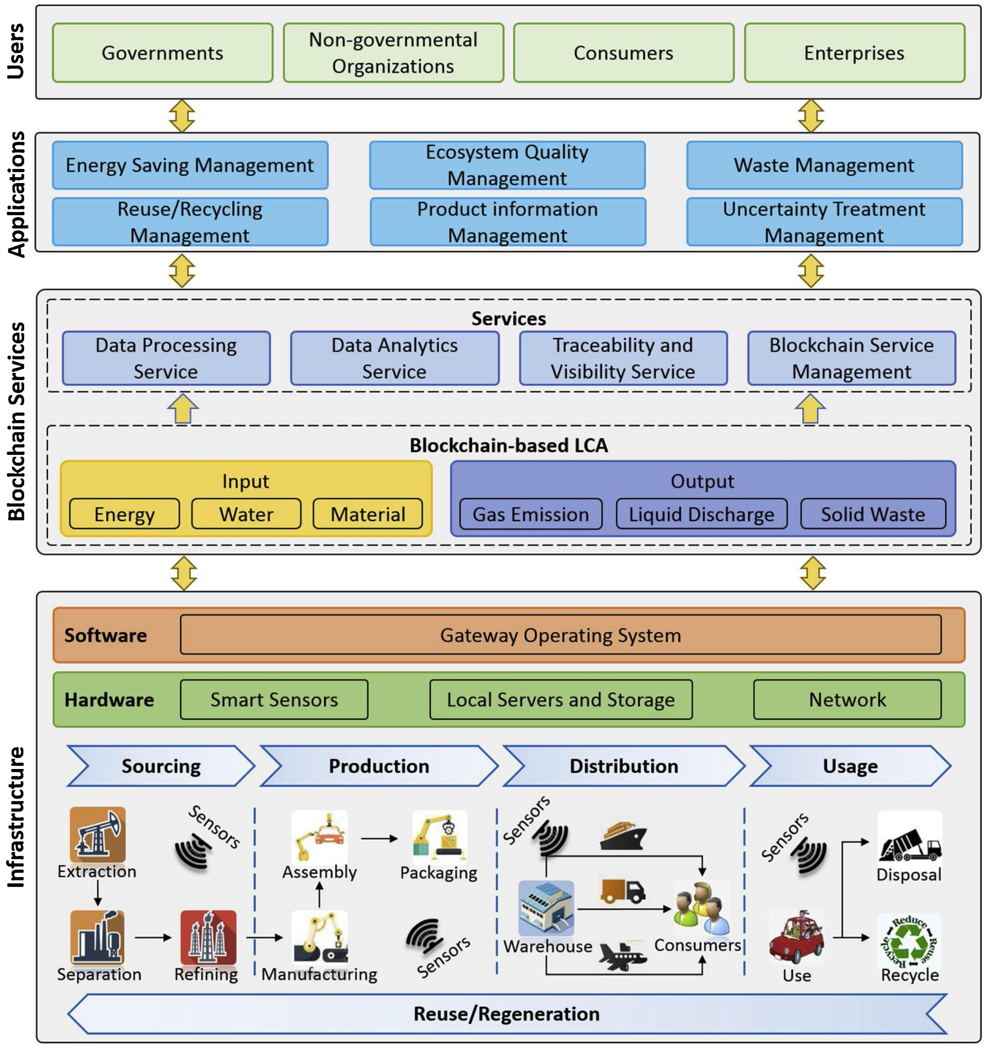

Figure 7. LCA system utilizing blockchain technology (taken from [80]).

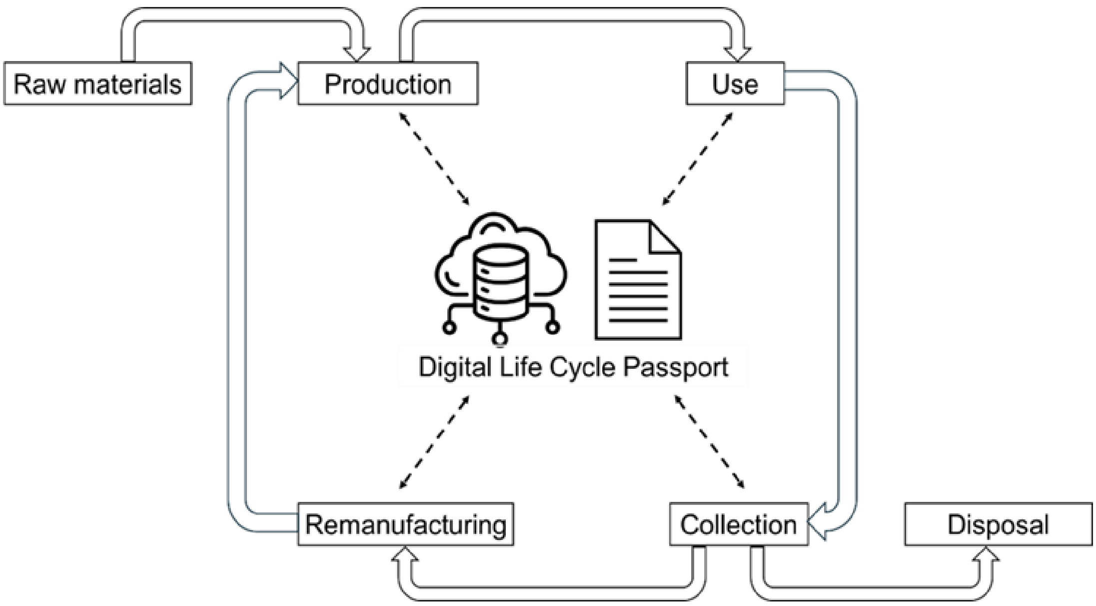

Figure 8. Data management via the digital life cycle passport (DLCP) (modified from [75]).

4.2. Scheduling and Planning

Effective scheduling and planning are essential for remanufacturing management as they ensure optimal resource allocation, minimize downtime, and enhance overall operational efficiency. To address the challenges of process complexity and demand uncertainties, data-driven optimization and RL models have been developed. Various types of uncertainties impact the scheduling and planning of the remanufacturing process. The most studied uncertainty is the quality of returned cores [55,61,62,93–95,97,98,103], which significantly impacts the remanufacturing process requirements, resource needed, and cost estimates. Another crucial uncertainty is the disassembly time [70,99,101,102], which affects process planning and resource management. Additionally, uncertainties related to the cores and demands [93,94,96] affect production planning and inventory management, with variations arising from differences in core return timing and quality [61,63]. Furthermore, remanufacturing failure rates [55,101,102] are crucial for robust process planning and quality assurance. While these uncertainties are well documented, others like the resources needed for remanufacturing [63], are less discussed.

ML and data-driven models are powerful tools to address the challenges in scheduling and planning, particularly through meta-heuristic, mathematical optimization, and RL techniques. Mathematical optimization techniques are utilized to maximize profit and minimize costs in scheduling and planning in remanufacturing. These methods typically target optimizing acquisition qualities and quantities, remanufacturing decisions, and resource allocation. For instance, Yang et al. formulated a convex optimization, an extended multi-product Newsvendor Problem, to maximize overall profit [62]. Similarly, a nonlinear integer programming (NLIP) model was developed to minimize the total cost of acquisition, remanufacturing, and scrapping of cores [63]. Other data-driven approaches integrate with linear programming to maximize total profit [62], applying nonlinear programming models considering carbon emissions [64]. The objectives of these models are often costs, revenue, and environmental benefits. Meta-heuristic techniques address complex, multi-objective optimization problems in scheduling and planning. Examples include a modified discrete BA for disassembly sequence planning [100], and an improved discrete BA for workstation optimization [28]. Zheng et al. proposed a GA combined with an improved random forest classifier to intelligently select the optimal rescheduling method based on system status, as shown in Figure 9. The system status is characterized by factors such as machine utilization, job processing times, and the total time required for reworked operations [101].

RL has proven to be effective in handling uncertainties in remanufacturing, such as the quality of returned products, machine failures, and varying initial states. Bai et al. used Q-learning and DQN algorithms to minimize total production time, continuously adapting to dynamic conditions [55]. Wurster et al. dynamically controlled a hybrid disassembly system, consisting of various types of stations, using DQN to minimize labor costs, idling costs, makespan, and failures [57]. Paschko et al. dealt with the control of job release in a hybrid disassembly line, minimizing work in progress and maximizing throughput using PPO [56]. Peng et al. employed PPO to optimize disassembly scheduling and minimize makespan, utilizing the strength of RL to adapt to various uncertainties and improve decision-making over time [103].

Hybrid approaches that combine multiple algorithms have also demonstrated effectiveness. For example, one study integrated fuzzy dynamic modeling and Monte Carlo simulations with RL for robotic disassembly optimization [70]. The combination of different techniques holds significant potential for developing robust and adaptive systems capable of navigating the dynamic landscape of remanufacturing scheduling and planning. Future research could focus on further integrating these approaches to leverage their respective strengths and address increasingly complex challenges in remanufacturing.

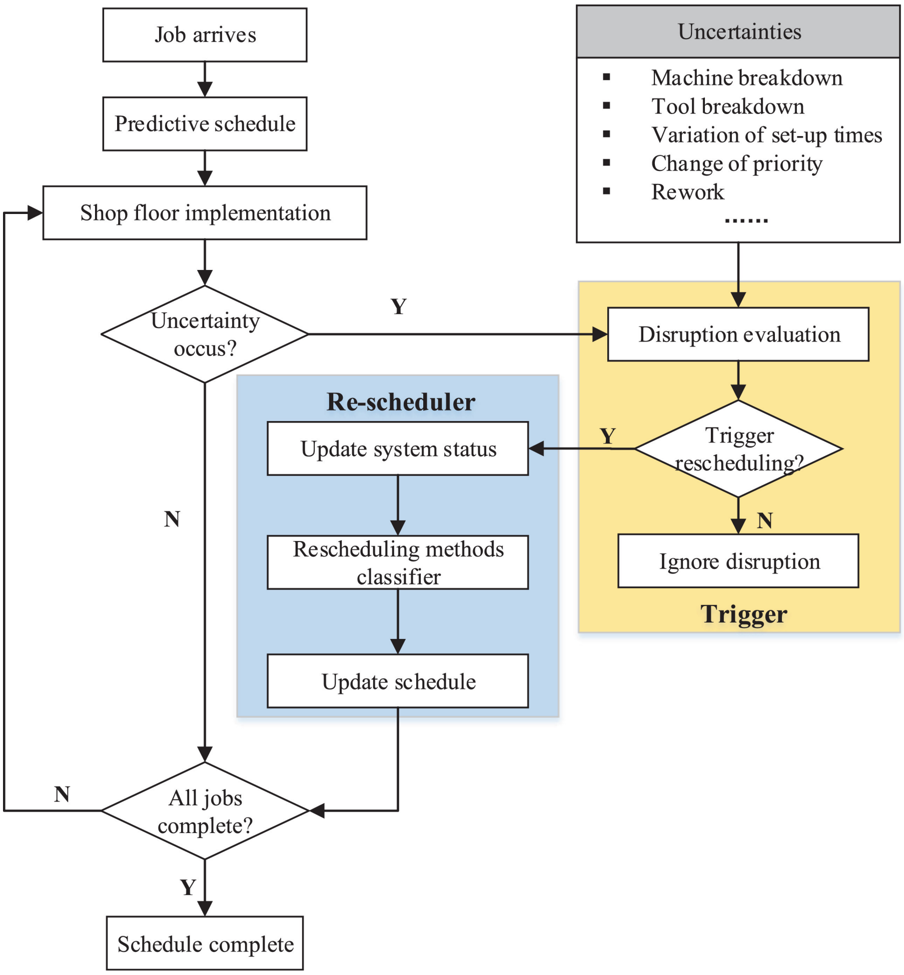

Figure 9. Flowchart of adaptive (re)scheduling strategy (taken from [101]).

4.3. Quality Control

Quality control in remanufacturing involves assessing and validating the condition of returned components or remanufactured products to ensure they meet specified standards before reprocessing or market release. Remanufacturing models in the literature often assume quality to be homogeneous; however, it has wide variations due to customer usage, usage length, and special product characteristics [133]. These variations make inspection processes in remanufacturing labor-intensive and time-consuming. Advanced computational methods, such as object detection and defect identification, can aid in evaluating the condition, reusability, and quality grade of returned cores, addressing the high uncertainty and subjective bias associated with manual assessments [134]. In this section, we review and categorize the literature on the use of data-driven and ML methods for automating remanufacturing quality control. These technologies help overcome issues related to individual subjectivity, time constraints, and high labor costs by excelling in learning complex geometries and patterns [135].

Kaiser et al. highlighted the challenges of high uncertainty in the inspection process related to cores and addressed these by utilizing RL models to capture cores, and an unsupervised learning model for anomaly detection [32], as demonstrated in Figure 10. The figure demonstrates the model capability of handling uncertainty in remanufacturing through its adaptable architecture. As shown in the figure, the model starts with processing, comparing the core's expected and inspected conditions. Deviations are flagged for review. Sensors capture data during the perception stage, which the quality controller analyzes for defects. Finally, during decision-making, the system decides if the core is reusable or should be rejected, automating the entire inspection process. Few-shot learning techniques were employed to categorize anomalies and to precisely assess the core's quality grade [32]. Nwankpa et al. presented a novel inspection process with a deep convolution neural network for mild steel plates to detect eight fault conditions and their combinations [105]. The high accuracy of the model on a small dataset demonstrated its robustness and efficiency, making it an ideal solution for smart inspection strategy in remanufacturing.

Islam et al. presented an automated sorting system utilizing a smart conveyor with multiple cameras, reflective sensors, and a PC running Python applications. It leverages inception transfer learning for image classification and the YOLO model for object detection, ensuring robust and high-accuracy identification and sorting of remanufacturing parts through the combination of classifiers [106]. Mongan et al. used a Gaussian process regression model to predict the performance of ultrasonically welded joints and unanticipated process variation based on the process inputs and feedback (integrated sensor data) [107]. The proposed method, capable of detecting process variations and anomalies, has proven effective in both manufacturing and remanufacturing environments. It enhances quality control by identifying anomalies throughout operations and enabling informed decisions regarding the reusability and remanufacturability of cores and parts.

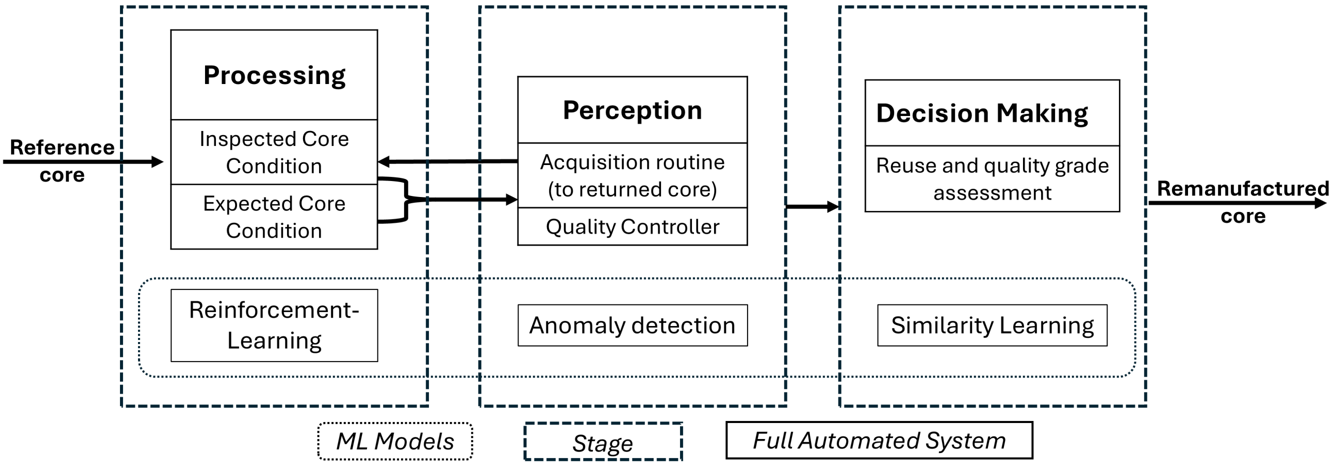

Figure 10. A scheme of core condition assessment through image and point cloud analysis, detecting quality deviations like corrosion or missing parts, which are then compared to expected conditions to determine reusability and quality grade (recreated from [32]).

In addition to implementing an effective inspection strategy for cores and remanufactured products, it is crucial to monitor various processes within remanufacturing operations. Statistical process control is a valuable tool for achieving process stability and reducing variability [136]. It facilitates continuous improvement and enhances quality assurance throughout the operations [137], which can be significantly augmented by ML models. ML excels in pattern recognition, allowing control charts to detect complex patterns, automate root cause analysis, and examine relationships between process data [108]. The integration of AI and ML into remanufacturing process control ensures adherence to high quality and standards. Moreover, the remanufacturing time of the equipment also influences quality standards and the economic effectiveness of remanufacturing decisions. Wang. et al. proposed a deep belief networks model to predict the optimal remanufacturing time by analyzing the historical equipment multi-life cycle and cost composition data [109]. The integrated automated inspection, condition monitoring and optimized planning and production can make the remanufacturing and maintenance plan more efficient and cost-effective [138].

In remanufacturing, it is necessary to define an optimal inspection plan following the identification of critical-to-quality parameters—key product characteristics (KPCs) and key control characteristics (KCCs) [139]. Product characteristics may be categorized into standard and key product characteristics. KPCs dictate quality parameters that could be determined through quality engineering tools and techniques such as Quality Function

Deployment, Failure Mode and Effects Analysis, Design for Manufacture and Assembly [140]. KCCs are established to precisely control them within specified limits to check variability within the processes to maintain both the process and KPC target values [141]. The remanufacturing scenario presents a complex challenge regarding the efficiency and effectiveness of inspection owing to the products designed and manufactured by some third-party enterprises and the high variability in the core inputs [142]. ML and data-driven models offer significant potential to improve parameter evaluation and maintain inspection efficiency in complex and variable remanufacturing scenarios [143].

4.4. HRC

HRC in remanufacturing enhances productivity and precision by merging human dexterity and decision-making capabilities with the consistency and strength of robots. This synergy not only boosts efficiency and adaptability to uncertainties but also holds promise for effectively managing process complexities and uncertainties in product disassembly, component inspection, and reassembly through the strategic allocation of tasks between humans and robots/cobots. This synergy forms effective teams with unique capabilities in operational tasks, information perception, and learning [144]. HRC enhances precision and adaptability in assembly [110], integrates human expertise with robotic sensing in inspection [58], and addresses the unpredictable challenges of disassembly. While full automation is often impractical, HRC enables efficient task distribution between humans and robots [114]. This approach addresses the unpredictable nature of returned products while balancing workload and economic outcomes. However, implementing HRC in remanufacturing systems faces challenges ranging from technological integration to worker adaptation and process changes [114].

In HRC for remanufacturing, process planning objectives include human-related factors alongside traditional profit-oriented goals like minimizing disassembly time, cost, and workstation numbers [28,59,70,95,99,100,115–118,122]. While efficiency remains crucial, its definition shifts in HRC scenarios. Instead of focusing solely on throughput and resource utilization, efficiency in HRC emphasizes optimal task allocation between humans and robots [28,59,100,115–118,122]. This addresses the challenges of workload distribution in manual and automated operations, as noted by [114]. Unique to HRC are objectives related to worker well-being, including human fatigue, safety, and workload [59,115–117,122]. These human-centric considerations are crucial in HRC scenarios, recognizing the importance of worker well-being and safety in the remanufacturing process. Environmental factors such as energy consumption are sometimes considered [59], further expanding the multifaceted nature of HRC in remanufacturing planning and scheduling. Balancing these diverse objectives makes optimal task allocation between humans and robots a central research question in HRC for remanufacturing.

ML and data-driven methods drive the utilization of HRC to enhance the efficiency and quality of remanufacturing processes. For example, Belhadj et al. conducted an extensive product analysis based on a CAD file to customize suitable operations for each returned core [119]. This has been extended to access the properties, complexity of parts and tool requirements [120]. Connecting elements are often of particular interest because their detachment affects the complexity and forces required for a remanufacturing operation, which, in turn, influences whether a task is best performed by a human or a robot [121]. To effectively allocate tasks in inspection, Karami et al. propose an AND/OR graph-based approach, improving efficiency by enabling parallel operations like simultaneous retrieval and inspection, allowing human intervention for issue management [58]. Another study implemented a voice-controlled collaborative inspection system where robots performed AI-powered visual inspections of predefined areas while humans provided oversight and performed parallel tasks, reducing the cycle time by 33.4% compared to manual inspection [113].

While the remanufacturing literature rarely focuses specifically on reassembly, research on general assembly has identified various ML and data-driven approaches for task allocation in HRC. Traditional methods such as Markov chains [71] and Petri nets [60] have been successfully applied, showing significant improvements in efficiency and cycle times. Figure 11 shows an exemplary workflow of HRC for disassembly designed to flexibly and efficiently complete the disassembly process in remanufacturing [100]. The disassembly process begins with establishing a model to define the disassembly precedence of products, allowing the generation of feasible disassembly sequences. Disassembly tasks are then classified, and the disassembly sequence for the robot and operator is optimized and evaluated based on time, cost, and difficulty [100]. Specifically, a prediction mechanism is employed to infer the human's current activity and anticipate their next assembly steps. The results from this algorithm are then fed into a scheduling algorithm, enabling the robot to determine its actions in a way that is both assistive and productive. Deep learning techniques like LSTM have been employed for multimodal recognition of subtasks in collaborative human–robot tasks [111]. Additionally, RL approaches have shown promise in adaptive task scheduling for interactive HRC assembly processes [112].

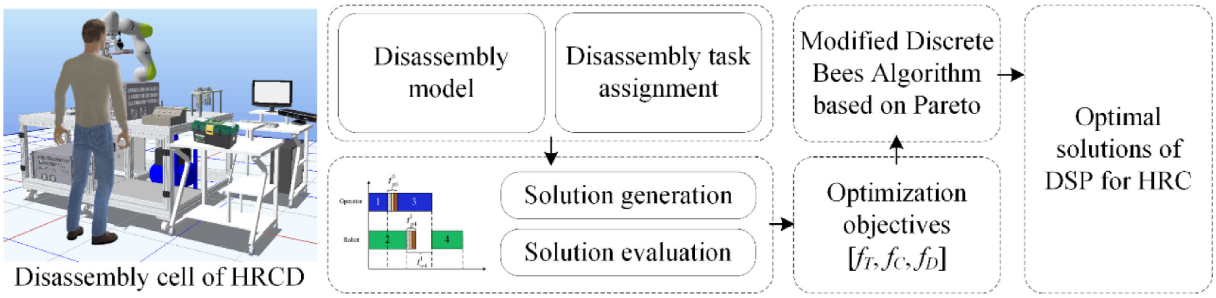

Figure 11. The workflow of HRC for disassembly (taken from [100]).

5. Discussion

The literature analysis reveals that integrating data-driven and ML models advances remanufacturing systems by enabling real-time monitoring, enhancing quality control, and facilitating dynamic scheduling, thereby supporting circular economy initiatives. Leveraging advanced sensors and connectivity, the IIoT and DPP enable comprehensive data collection and analysis across various stages of the remanufacturing process. Data-driven models derived from IIoT data play a vital role in supporting LCA and closed-loop supply chain management. They provide a thorough evaluation of environmental impacts throughout the product life cycle and aid in making informed decisions to promote sustainability. This capability provides critical insights into operational performance and product life cycle management. It is particularly effective in addressing uncertainties associated with the timing, quality, and quantity of returned parts, which significantly impact inventory control, product design, and production planning for remanufactured products [145].

Advanced ML techniques, such as deep learning and RL, further refine this process by enabling precise defect detection, anomaly management, and dynamic scheduling, thereby addressing uncertainties and improving operational effectiveness. For example, CNNs and YOLO models can be used in automated quality inspection systems to analyze images of remanufactured components, detecting defects with high accuracy, reducing inspection time, and ensuring consistent adherence to quality specifications. Predictive analytics can forecast potential failures, allowing for preemptive interventions that minimize operational disruptions and associated costs. RL optimizes dynamic scheduling and operational strategies to address uncertainties effectively. These advanced techniques not only improve operational effectiveness but also ensure that remanufactured products meet high standards of quality and reliability.

From the literature review, it is understood that, despite their advantages, the implementation of data-driven and ML methods in remanufacturing presents several challenges and may require the comprehensive adoption of smart manufacturing technologies. Smart manufacturing technologies utilize cutting-edge solutions, such as the IIoT, AI, ML algorithms, advanced sensor networks, and cyber-physical systems, to create digital simulations of production processes, manage computer-controlled equipment, and track and report real-time production data [146]. ML and data-driven models, as part of smart manufacturing techniques, support predictive maintenance, and analytics, enabling more accurate control and optimization of manufacturing processes [147]. Existing studies have discussed smart manufacturing in support of environmental sustainability. Huang et al. reviewed the literature on Industry 4.0, emphasizing its potential to enhance manufacturing sustainability through interconnected, smart technologies. The review examines how internet-connected machines and sensors improve productivity, energy efficiency, and environmental impact by optimizing processes and reducing waste [37]. Sutherland et al. reviewed recent research on the environmental impacts of industrial activities, focusing on work from the past 10–20 years, organizing their findings around the product life cycle and key topics in environmental impact [148]. Their review also systematically summarizes challenges in design, process improvement, and material efficiency within the framework of a circular economy, all within the context of Industry 4.0 advancements [148]. Kara et al. reviewed the evolution of emerging information and communication technologies to enhance material efficiency and environmental sustainability, adopting a holistic approach that redefines human–nature relations within planetary boundaries [149]. In this study, we further investigate the opportunities offered by smart manufacturing in remanufacturing, as illustrated in Figure 12, emphasizing how the integration of data-driven and ML methods with advanced manufacturing technologies can significantly enhance remanufacturing practices.

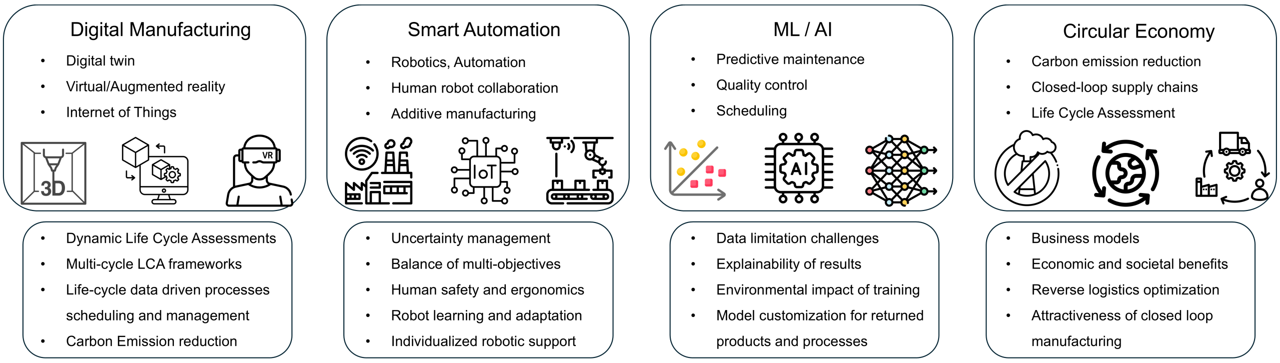

Figure 12. Future research directions in using smart manufacturing technologies for remanufacturing.

Developing smart manufacturing methodologies for dynamic LCA is essential for providing real-time feedback on the environmental impacts of remanufacturing processes. Identifying effective methods for measuring and reducing carbon emissions, as well as creating new LCA frameworks that capture the long-term benefits of remanufacturing across multiple life cycles, is crucial. Digital manufacturing technologies significantly enhance remanufacturing processes by enabling dynamic LCA that provides real-time feedback on environmental impacts, allowing for immediate adjustments to improve sustainability. These technologies also support the development of multi-cycle LCA frameworks, which accurately capture the long-term benefits of remanufacturing across multiple product life cycles. Additionally, life-cycle data-driven scheduling and management optimize processes by leveraging detailed insights into product histories to improve efficiency and decision-making. Moreover, digital tools play a crucial role in reducing carbon emissions by identifying and mitigating inefficiencies in processes and logistics, contributing to more environmentally responsible remanufacturing practices.

For remanufacturing system automation, it is important to balance conflicting objectives, such as profit maximization, cost reduction, environmental benefits, and adaptability to real-time changes and uncertainties. Furthermore, enabling robots to effectively learn from human operators and developing adaptive robotic support systems tailored to individual worker's skills, work styles, and ergonomic needs are critical. Additionally, using AI and ML in remanufacturing presents several significant challenges. One key challenge is the curation of data. Unlike in other manufacturing applications where data are often assumed to be complete due to the continuous monitoring and collecting from mass production lines, remanufacturing deals with highly heterogeneous data spanning a wide range of temporal scales, core specifications, and process requirements. This diversity makes it extremely difficult to align and fuse data to build the necessary context for effective AI analysis.

The explainability of results is another critical issue, as many AI models, particularly complex ones, operate as "black boxes", making it difficult to interpret their decisions and ensure they align with industry standards and expectations. The environmental impact of training is also a concern, as training sophisticated AI models can require substantial computational resources, leading to significant energy consumption, substantial data computing/storage costs, and a larger carbon footprint. Finally, model customization for returned products and processes poses a challenge. AI systems need to be tailored to handle the variability and complexity of returned items and diverse remanufacturing processes, which can vary greatly in terms of quality and characteristics. Addressing these challenges is essential for effectively integrating AI and ML into remanufacturing. To address remanufacturing challenges, cohesive models should integrate automated inspection, production planning, and time prediction, with a focus on low data storage and computational efficiency to support enterprises in different scales. Research may also target effective predictive maintenance methods, anomaly detection algorithms, and model architecture design and optimization to customize models for diverse products and processes.

Applying digital technologies to remanufacturing could focus on exploring innovative business models that enhance economic competitiveness while offering societal benefits. These models might leverage the circular economy by promoting closed-loop manufacturing practices, helping to reduce waste, conserve resources, and create sustainable jobs. Additionally, research could aim to optimize reverse logistics through digital solutions, potentially improving the efficiency of handling returned products by refining inventory management, reducing transportation costs, and enhancing product quality control. Such efforts could be important for demonstrating the economic and environmental benefits of closed-loop manufacturing, thereby increasing its attractiveness and encouraging broader industry adoption. Moreover, future studies could consider using life cycle data to further refine process optimization and emphasize economic advantages, while also considering the broader economic, environmental, and social benefits of closed-loop supply chains in remanufacturing.

The potential of integrating data-driven and ML methods into remanufacturing extends well beyond the computational techniques examined within the smart manufacturing framework. The advent of emerging advanced manufacturing technologies, when coupled with these data-driven and ML methods, unveils opportunities that remain largely untapped. Additive manufacturing (e.g., 3D-printing) offers significant benefits for remanufacturing by enabling the rapid repair of damaged components and the production of custom parts on demand [150,151]. This technology allows for precise material deposition and can create complex geometries that traditional manufacturing methods cannot easily achieve, potentially reducing lead times and lowering costs. Laser cladding, another advanced technology, provides a method for adding material to worn or damaged surfaces with high precision, restoring parts to their original dimensions and enhancing their performance [152]. Significant challenges involve addressing material compatibility issues in advanced manufacturing processes, overcoming barriers to fully automating remanufacturing systems. Data-driven models enhance this process by accurately predicting material properties and optimizing process parameters, while ML supports the customization and personalization of parts and improves quality control through real-time defect detection [153]. Together, these integrated approaches hold great promise for advancing the efficiency and sustainability of remanufacturing processes.

6. Conclusions

In this study, we investigated the integration of data-driven and ML technologies into remanufacturing processes to improve both operational efficiency and sustainability. Our findings highlighted how technologies such as the IIoT and DPP facilitate real-time monitoring, thereby supporting real-time LCA and closed-loop supply chain management. We further explored advanced ML techniques for precise defect detection, anomaly management, and process optimization. Additionally, we evaluated the impact of dynamic scheduling and HRC on mitigating uncertainties in remanufacturing. This research review effort not only identifies key gaps and challenges but also uncovers opportunities for advancing remanufacturing practices through advanced computational methods and smart manufacturing technologies, emphasizing their potential to deliver economic, environmental, and societal benefits.

Future work should focus on providing clearer categorizations of the challenges and pros and cons of ML and data-driven methods in remanufacturing, along with guidelines for selecting the most effective AI techniques for specific problems. Additionally, summarizing and comparing various AI applications in remanufacturing, providing practical examples of AI adoption in remanufacturing, would also be valuable for industry practitioners and researchers. Furthermore, future research should also explore the human-centric benefits of advanced computational algorithms and smart manufacturing technologies, considering not only personal well-being but also higher-level human needs, such as personal growth and self-actualization. This approach will ensure that advanced computational algorithms contribute positively to the workforce and create broader societal benefits.

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