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A comprehensive review on human–robot collaboration remanufacturing towards uncertain and dynamic disassembly

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Abstract. With the continuously increasing volumes of End-of-Life (EOL) products and the emergence of Industry 4.0-related technologies, the manual labor-intensive disassembly in remanufacturing process is gradually shifting towards human–robot collaboration (HRC) disassembly. However, it is necessary to consider the most commonly approach in current robot-involved automatic disassembly with the high efficiency and adaptability. The purpose of this paper is to summarize the existing human–robot collaboration disassembly technologies to further discuss the possible applications of various technologies in the disassembly process, thereby providing the comprehensive reviews of future research directions. The paper presents an analysis of the technical issues encountered in the HRC disassembly process, which provides a summary of the intelligent disassembly platform with robot agents as the core, focusing on the optimization of HRC disassembly. Furthermore, the relevant technologies are reviewed to discuss the intelligent disassembly systems, including Cyber-Physical systems (CPS), Internet of Things (IoT), Cloud Computing, Artificial Intelligence (AI), and Digital Twins (DT). The industrial applications of various optimization methods have discussed the potential research trends in the collaboration of multiple robots and humans in disassembly with the perspectives of task allocation, collaborative decision-making, and performance evaluation, focusing on the application trends of digital twin technology in industrial disassembly lines.

Keywords: Human–robot collaboration / disassembly / industry 4.0 / digital twin / uncertainty

1 Introduction

With the increasing global development of sustainability and environmental protection, industrial green manufacturing has become increasingly urgent. Simultaneously, the demand for green products by consumers has been rising, which facing with the recycling of End-of-Life (EOL) products to subsequently develop the gradual emergence of the remanufacturing industry [1]. Remanufacturing involves the repair, refurbishment, or disassembly/reassembly of products to restore their original functionality or meet new product requirements, thereby extending product lifespans to reduce environmental impacts. Remanufacturing products can be priced up to 50% lower than new products [2] to provides the consumers with more attractive options. However, it is necessary to not only protect the environment to achieve efficient resource utilization, but also provide strong impetus for economic and social sustainability.

However, remanufacturing process typically includes six stages: product recovery, initial inspection, disassembly, component repair, reassembly, and performance testing [3]. Disassembly, as one of the most key steps in the remanufacturing system, holds significant value to accomplish the green manufacturing in the recycling. With the increasing volumes of EOL products, there is a need to achieve full or partial automation of disassembly process to improve efficiency in the remanufacturing process [4]. Due to the uncertainty associated with EOL products and the requirements of completely automation production, the implementation of fully automation disassembly lines remains many challenging [5,6]. Similarly, the semi-automated disassembly lines offer new approaches to improve disassembly efficiency according to their low investment costs, strong flexibility, and good adaptability [7]. The typical semi-automated disassembly mainly focuses on human–robot collaborative (HRC) disassembly, where human operators and robots agents jointly in the disassembly operations to achieve accurate disassembly of EOL products. Similarly, the HRC modes in disassembly can be divided into three types as follows:

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– Sequential disassembly: as a process of gradually disassembling products in a specific order, typically used for more structured and orderly disassembly tasks.
– Parallel disassembly: as simultaneous disassembly of multiple components, involving different personnel or robots to enhance disassembly efficiency.
– Collaborative disassembly: as a mode where humans and robots cooperate in disassembly, leveraging each other's strengths to enhance overall disassembly efficiency and safety. These three forms of disassembly each have their own advantages to different disassembly scenarios.

By comparing the traditional disassembly processes, the new disassembly methods based on HRC operations are faced with the higher safety risks and the stricter recycling requirements [8]. Collaborative work by human operators and robot agents in the same working space may generate the risks of collision and entanglement, especially in the compact spaces, potentially leading to accidents. Therefore, safety constraints are typically added in the planning of collaborative disassembly. With the continuous development of Industry 4.0, intelligent technologies such as cyber-physical systems and cloud computing are gradually being introduced into the remanufacturing process. Considering the requirements of addressing the uncertainty of EOL products and collaborative safety, digital twinning technology is gradually being introduced into the HRC disassembly process. The digital twinning technology was first proposed by Professor Grieves in 2002 and refers to the interaction of real-time digital models with physical entities (products, equipment, systems, or processes) to monitor, analyze, and optimize their operational status. Digital twinning not only reflects the geometric features of physical entities, but also encompasses their operational status, behavior, and performance. This technology enables comprehensive simulation, predictive maintenance, and performance optimization of physical entities to facilitate real-time decision supports. The applications of digital twinning technology can identify potential hazards and risk scenarios to predict possible risk situations, which help to take preventive measures, thus enhancing the safety of collaborative disassembly. Furthermore, the other decision-making technologies (i.e., reinforcement learning, neutral networks, etc.) [9] can provide the specific solutions to combine HRC disassembly with flexibility and efficiency. This paper aims to review the relevant application techniques for multi-agent HRC disassembly. The related literatures were retrieved from the Web of Science, Science Direct, and IEEE Xplore databases, etc., including the journal papers and the conference papers according to the specific reviewing procedure as shown in Figure 1.

2 Scientific challenges towards intelligent disassembly

In the remanufacturing fields, intelligent robots are working alongside human operators to perform remanufacturing tasks such as assembly, disassembly, and CNC machining [10]. The continuous development of automation and intelligent technologies has enhanced the flexibility and adaptability of the industrial robots in remanufacturing process, thus achieving the closer HRC disassembly. With the recent advancements of the intelligent collaborative technologies, remanufacturing process can be used to improve the potential values of EOL product. However, the diversity of EOL products has brought out the impact of the uncertainty, leading to increased complexity of HRC disassembly, while also affecting overall time and cost. Therefore, it is essential to summarize the scientific challenges of HRC disassembly technologies.

2.1 Uncertain product quality

Almost all the EOL products undergo disassembly to accomplish the potential value of EOL product recycling with the uncertainty of end-of-life products, which makes the human–robot collaboration disassembly strategy need to dynamically optimize in real time disassembly processes or sequences. Rickli et al. [11] proposed the impact of uncertain EOL product quality and the optimal disassembly sequences to establish a correlation between the aging distribution and their quality, which introduced a mathematical framework to assess the optimal disassembly sequence by analyzing the partial disassembly sequence in age distribution of EOL products. The uncertainty of EOL products poses many challenges to the development of an optimal disassembly process planning system with the quality uncertainty of EOL products, which can be used to address the uncertainty by optimizing the disassembly process. Zhu et al. [12] developed a comprehensive disassembly framework by combining an ontology-based information model, which simultaneously demonstrated the possible optimization of self-adaptive disassembly planning. Tian et al. [13] proposed a fuzzy perspective approach to analyze the uncertainty of disassembly process that combines fuzzy simulation and artificial bee colony methods. Empirical evidence has shown that the algorithm can generate superior solutions through subsequent fuzzy simulations. Laili et al. [14] proposed an interference probability matrix to represent the EOL product in the disassembly process by establishing a multi-threshold optimization of disassembly sequencing. The quality defects of end-of-life (EOL) products in the disassembly process mainly include the wear, deformation, corrosion, aging, etc. Meng et al. [15] proposed a multi-constraint remanufacturing disassembly line balancing model to address multiple failure and material hazard constraints, which integrates different engineering aspects (i.e., product failure modes and failure degrees), while demonstrating the efficiency of remanufacturing disassembly line systems.

The uncertainty of product quality might cause the variability of disassembly time for disassembly tasks, which causes the disassembly line balance problem (DLBP) for EOL product recycling as shown in Table 1. It is necessary to compare the various research points based on various optimization and decision-making methods for HRC disassembly process, including expected disassembly times, profit from disassembly, operation safety, and

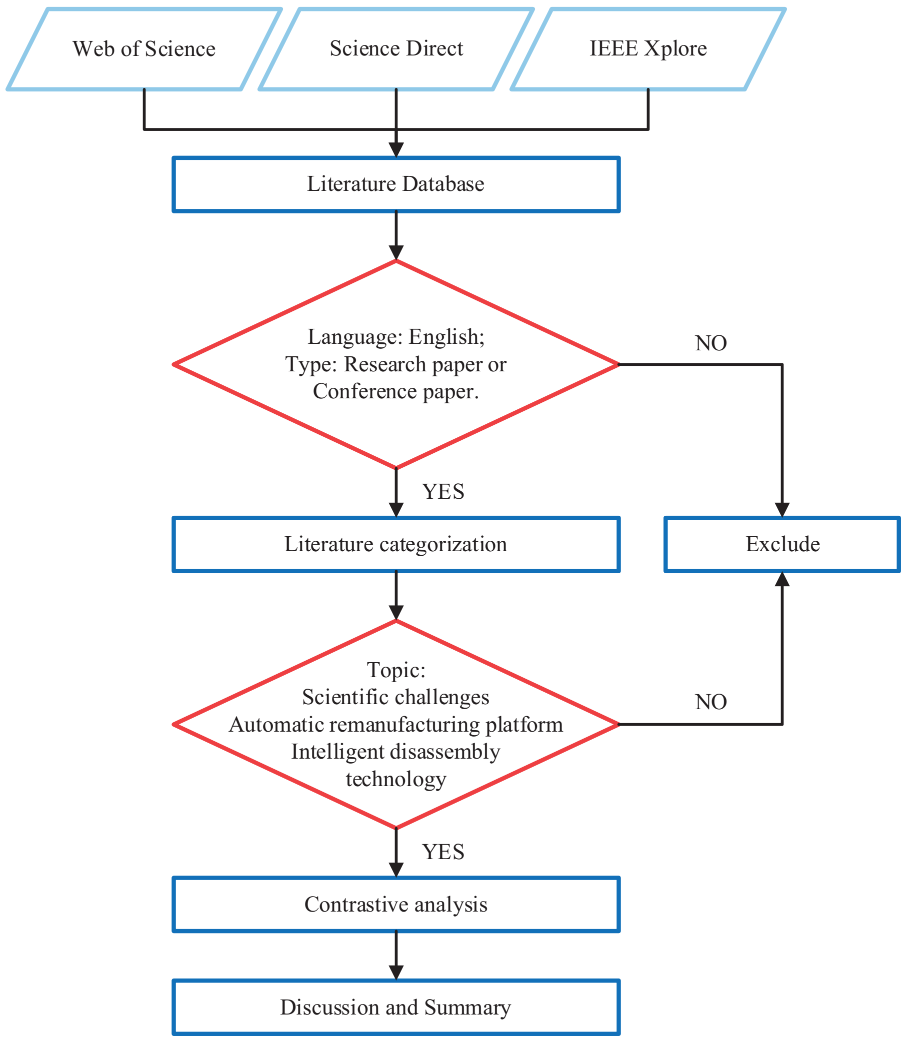

Fig. 1. The procedure of reviewing the related journal and conference papers.

Energy consumption of disassembly equipment. To address the correlation between uncertain disassembly tasks, Liu et al. [16] proposed a novel distributed robust analysis model with joint multi-constraints to optimize disassembly line balance. Zhang et al. [17] focused on energy consumption to present the stochastic energy consumption disassembly line balance problem (SEDLBP), which constructed a spatial interference matrix for SEDLBP analysis perspective. Furthermore, Liu et al. [18] addressed stochastic optimization in disassembly sequence planning by proposing an improved peacock optimization algorithm to explore optimal disassembly sequences. By considering the requirements of EOL product recycling to enhance the recovery efficiency and reduce the recycling costs, it becomes imperative to identify an appropriate recovery mode and HRC disassembly procedure. Xiao et al. [19] proposed a multi-agent reinforcement learning method for retired electric vehicle (EV) batteries, which discusses the potential for future hierarchical utilization and disassembly of EV batteries toward uncertain disassembly and hierarchical application scenarios. To tackle this challenge effectively, Yin et al. [20] proposed a novel HRC flexible remanufacturing system that enables practical battery disassembly production lines.

2.2 Disassembly dynamic structure

The diversity of disassembly products presents the significant uncertainty of the HRC disassembly process, thereby causing the challenging of complex disassembly tasks. As considering the variety of disassembly objects, dynamic disassembly is becoming as key scientific problems in the disassembly structure [31]. The disassembly representations such as Petri nets, AND/OR diagrams, and direct diagrams can be used to deduce the possible disassembly roadmap as shown in Table 2.

The comprehensive literatures were reviewed by analyzing the specific research points based on the application methodologies. Singh et al. [32] enhanced the disassembly Petri Net model, and subsequently developed the Expert Disassembly Petri Net and the Expert Enhanced High-Level Coloured Disassembly Petri Net.

Table 1. Reviewing the related literatures for HRC disassembly.

HRC disassembly optimization methods	Ref.	Research contents	Main concerning research points			
			Expected disassembly time	Profit from disassembly	Operator safety	Energy consumption of disassembly equipment
A mathematical optimization framework based on standard deviation and profit probability.	Rickli et al. [21]	• Analyze the expected profit of disassembled products. • Determined optimal disassembly sequence with GA algorithm.		√		
A disassembly information framework with ontology-based information model.	Zhu et al. [22]	• Develop information models and computational models by using product uncertainty.		√		
A novel hybrid intelligent algorithm integrating fuzzy simulation and artificial bee colony.	Tian et al. [23]	• Evaluate the uncertainty with fuzzy simulation. • Determined the optimal disassembly sequence with ABC algorithm.		√		
A multi-threshold scheme based on interference probability matrix.	Laili et al. [24]	• Established IPM to reflect uncertainty in interference conditions. • Multi-threshold sequence planning using IPM.	√	√		
A novel multi-constraint disassembly line balancing model.	Meng et al. [25]	• Construct MC-RDLB Mathematical Model. • Solve MC-RDLB by using NSGA-II algorithm.		√	√	
A new distributionally robust analysis with a joint constraint.	Liu et al. [26]	• Propose a distributionally robust joint chance-constrained formulation. • Propose Two-stage parameter-adjusting heuristic.	√			
A mathematical model of SEDLBP based on spatial interference matrix disassembly.	Zhang et al. [27]	• Constructs mathematical model of SEDLBP based on the disassembly of spatial interference matrix. • Solve SEDLBP by using stochastic simulation.	√			√
An improved peafowl optimization algorithm.	Liu et al. [28]	• Construct multi-objective mathematical model. • Construct IPOA algorithm framework.	√			

Table 1. (continued).

HRC disassembly optimization methods	Ref.	Research contents	Main concerning research points			
			Expected disassembly time	Profit from disassembly	Operator safety	Energy consumption of disassembly equipment
Hierarchical analysis methods based on various battery evaluation index.	Xiao et al. [29]	• Analysis technical standards for EV batteries Echelon Utilization. • Analyze the EV batteries disassembly planning method.		√	√	
A novel human–robot collaborative flexible remanufacturing system.	Yin et al. [30]	• Analyze the kinematics of collaboration robot with D-H parameter method. • Planning trajectory of collaboration robot with RRT algorithm.			√	

By considering the high-efficient disassembly points as an example, these three methods were compared to demonstrate their practicality in disassembly sequence planning. Turowski et al. [35] proposed a Fuzzy Coloured Petri Net model to characterize the influence of uncertain disassembly factors based on heuristic algorithms to balance the disassembly lines. In their subsequent scientific research, an adaptive fuzzy system was proposed by an enhanced learning method for predicting environmental impacts [36]. Tang et al. [37] considered product uncertainty caused by human intervention in the disassembly process to represent the effects of membership functions, which addressed the disassembly optimization by developing a fuzzy attributed Petri net model. In their further research, Tang et al. [38] proposed an enhanced fuzzy learning algorithm with variable memory length to ensure the robustness of adaptation processes. Similarly, Tian et al. [39] analyzed the uncertainty of evaluation algorithms for disassembly indicators with the fuzzy sets to represent the structure information, thereby transforming Petri net models into fuzzy analysis method. Therefore, the different characteristics of disassembly optimization methods can be compared as shown in Table 3.

However, Mendez et al. [40] proposed the direct and indirect graph to represent the product structure that determines the optimal disassembly sequence. Edmunds et al. [33] proposed a constraint-based method to investigate the optimal disassembly sequences by transforming the AND/OR structure into a precedence structure. Tian et al. [41] highlighted that the existing heuristic disassembly planning to adequately address the structure relationship with a triple-phase adjustment method that integrates conflict matrix, precedence and succession matrices to explore a feasible disassembly sequence. In addition, to address these dynamic disassembly problems, Zhu et al. [42] incorporated dynamic disassembly capabilities into the information model to accommodate the disassembly operations, which subsequently discussed an optimization model. Ye et al. [43] integrated a fuzzy and dynamic modeling method with an iterative re-planning strategy to enhance the adaptability of disassembly planning process. Furthermore, by exploring artificial intelligence and machine learning as potential solutions for these challenges, Meng et al. [44] synthesized key advancements and research opportunities in emerging smart technologies for recycling and reuse of industrial products, with a particular emphasis on resolving uncertainty issues. Therefore, it is necessary to combine with the artificial intelligence and with HRC disassembly, which can effectively address such uncertainties and significantly improve the adaptability of disassembly processes.

3 Automatic disassembly in remanufacturing

With the continuously increasing volumes of End-of-Life (EOL) products, traditional labor-intensive manual disassembly is no longer able to meet the efficiency requirements for disassembly towards semi-automated disassembly. Semi-automated disassembly, compared to manual disassembly, offers multiple advantages including disassembly efficiency, cost reduction, disassembly safety, and environmental protections. With the sustainable development of

Table 2. The comparison between disassembly structure representations and their characteristics according to the related papers.

Disassembly structure representation	References.	Advantages	Disadvantages
Petri Net	Singh et al. [32]	Effective concurrent behavior and resource competition. simulation and quantitative analysis.	Complexity in modeling and analysis for complex scenarios. Limited capability.
AND/OR Graph	Edmunds et. al. [33]	Clear representation of task dependency. Relatively intuitive and simple implementation.	A large structure in complex scenarios. Lack of capability in resource constraints.
Direct Graph	Mendez et al. [34]	Clear representation of disassembly task sequential relationship. Easily transformed into execution paths.	Limited capability Ambiguity and complexity

Table 3. The different characteristics of disassembly optimization methods.

Optimization methods	Colour identification	Influence	Probability	Average profit	Operation time
DPN					
EDPN		√	√		
EEHLCDPN	√	√	√		
FCPN	√	√		√	√
FAPN		√		√	√

Note: DPN/ Disassembly Petri Net; EDPN/ Expert Disassembly Petri Net; EEHLCDPN/ Expert Enhanced High-Level Coloured Disassembly Petri Net; FCPN/ Fuzzy Coloured Petri Net; FAPN: Fuzzy attributed Petri net.

modern remanufacturing fields, collaborative robots, as a core tool of semi-automated disassembly, play a crucial role on in automation, precision operations, data collection, and analysis. Therefore, it is necessary to provide a review and analysis of robot-assisted disassembly technology and human–robot collaboration disassembly technology as shown in Figure 2.

3.1 Robot-assisted disassembly

To achieve the autonomous disassembly based on robot-assisted remanufacturing, it is necessary to reduce the current manual disassembly owing to its time-consuming and lower efficiency of disassembly. Moreover, the disassembly of certain EOL products may cause the generation of hazardous materials, which is an inevitable trend for robots to assist the disassembly production lines. To address these challenges, Billard et al. [45] discussed the possibility of robot and human operators together to manipulate disassembly objects. Caiza et al. [46] considered the remote control to accomplish the disassembly operations of robot as the operators to minimize the potential operation risks. The robot-assisted disassembly has commenced to develop the gradual advancement for automatic production line as shown in Figure 3. Weigl et al. [47] emphasized the significance of robot-assisted disassembly in EOL product recycling, conducting a disassembly experiment with a camera as the object. Hohm et al. [48] explored the feasibility of robot-assisted disassembly on standard PC hardware, which focused solely on opened PCs for the disassembly process. Wegener et al. [49] devised a battery disassembly workstation to disassemble the EOL batteries from electric vehicles, focusing only simple and repetitive disassembly tasks with robot operations, while the complex disassembly tasks still relied on skilled human operators. The manual disassembly in the semi-automatic/ automatic disassembly production line should be implemented gradually. The automatic disassembly of industrial EOL products is typically significant to demonstrate the economic performance to manual disassembly [50]. In hazardous disassembly and recycling process, it can reduce the dependence on labor-intensive human works to improve the efficiency of EOL product recycling [51]. Because the uncertainties of current fully automated disassembly line development are more difficult, the current subsequent disassembly technology should be more attention on the development of intelligent collaborative disassembly. Foo et al. [6] demonstrated that there exists a significant correlation between the automation level and the disassembly capability to solve uncertain disassembly while exploring cognitive robots and semi-automatic disassembly. By reviewing relevant literature published in the past decade, it is necessary to compare the number of journal or conference papers related to human–

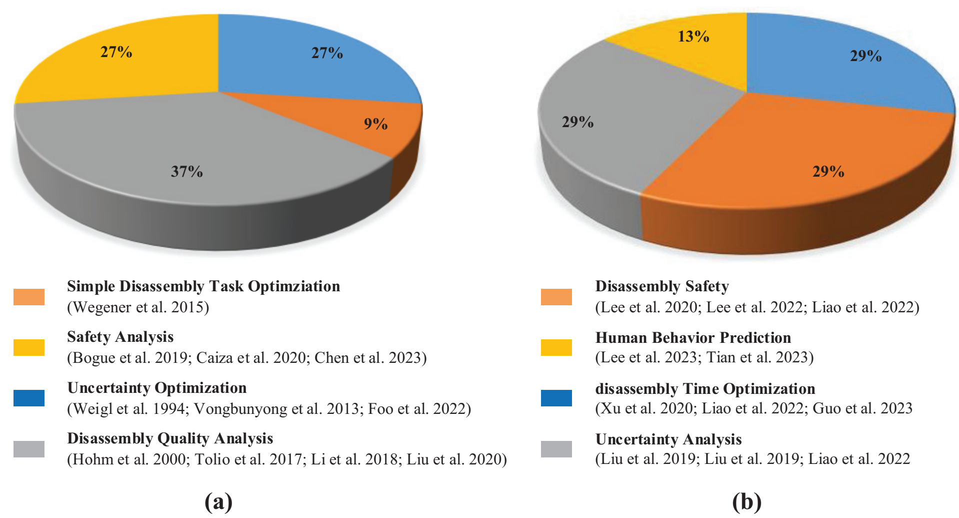

Fig. 2. Statistical proposition of (a) robot-assisted disassembly (b) human–robot collaboration disassembly in the remanufacturing process.

robot collaborative disassembly. In fact, in 2019, the number of papers specifically focused on human–robot collaborative disassembly exceeded those related to robot-assisted disassembly. This finding demonstrates that the greater potential of human–robot collaborative disassembly can be used to improve the efficiency, safety, and economic benefits of the disassembly processes.

3.2 Human-robot collaboration disassembly

The disassembly process towards uncertain disassembly objects has many intricate and diverse disassembly operations by considering the applications of HRC for safer, more efficient, and time-saving disassembly operations [52]. With the gradual capabilities of robot perception, HRC disassembly has become a feasible method to support the intelligent disassembly. Liu et al. [53] proposed a hybrid HRC disassembly framework that encompasses the perception, cognition, and decision-making to address the uncertainties and dynamics relationships in the disassembly process. The feasibility of disassembly system has been validated through subsequent case studies, which also integrate the advanced technologies such as cyber-physical production system (CPPS), artificial intelligence (AI), etc. The researchers further presented a machining learning-based method for predicting human motion using visual signals without any specialized wearable devices while still enabling effective human–robot interaction based on Digital Twin (DT) [54]. Although HRC disassembly effectively handles the uncertainty in the disassembly process, the human operator can impact the robot actions when compared to fully automatic disassembly. Lee et al. [55] proposed a disassembly sequence planner for human operator safety with multiple constraints to co-robots, which demonstrated that the robot can successfully complete its disassembly tasks to safety constraints through a simulated disassembly experiment. Subsequently, a real-time disassembly sequence planner also prioritizes the disassembly safety, which enables real-time identification of item locations, direction for disassembly, and operator positioning for optimal disassembly planning [56]. During the entire disassembly process, the disassembly operation action may also result in frequent interruptions to the robot, thereby reducing overall disassembly efficiency. Accurate disassembly behavior can minimize the robot idle time to consequently enhance the efficiency of disassembly. Lee et al. [57] considered that disassembly operation actions would interfere with robot actions by a sequence planner to predict the potential human actions that can be used to optimize task allocation by considering the human actions and real-time product status. Ding et al. [58] developed a knowledge-based platform for storing disassembly data, which provides the disassembly methods for robots to reduce the human workloads that helps reduce robot idle time and improve overall efficiency. Tian et al. [59] proposed a rational prediction model to analyze human behavior and motion based on an HRC dataset of disassembly tasks with the optimal disassembly processes.

To reduce the disassembly time of EOL products, it is necessary to improve the overall disassembly efficiency, which involves the balance of HRC disassembly lines for reasonable task allocation with optimal disassembly sequence. Xu et al. [60] proposed an enhanced discrete bees algorithm (MDBA-Pareto) based on Pareto optimization to determine the optimal solution for all feasible disassembly sequences. Guo et al. [61] developed an AND/OR structure graph to demonstrate the disassembly process combining with a HRC disassembly task times, which addressed it using a Pareto improved multi-objective algorithm. To further enhance the performance of disassembly optimization algorithm, it is necessary to optimize the disassembly strategy into the global disassembly process. However, the future HRC disassembly is expected to enhance the intelligence of collaborative robots, thereby improving the efficiency and safety of the entire disassembly process. Similarly, there are still significant potentials for research on HRC disassembly

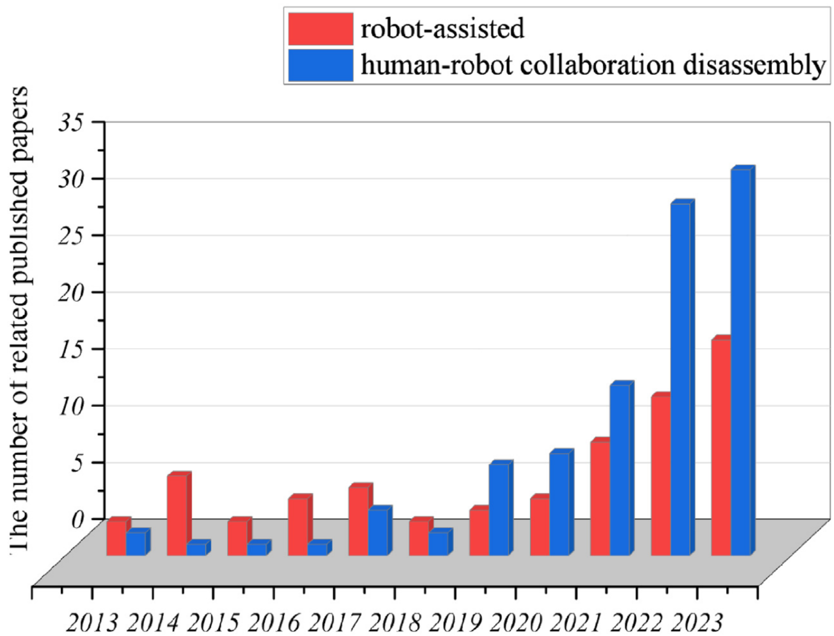

Fig. 3. Comparison of the number of related published literatures.

strategies, with artificial intelligence technology and digital twin technology potentially to accomplish the new breakthroughs [62].

4 Intelligent disassembly technology towards Industry 4.0

The development of Industry 4.0 or even Industry 5.0 has brought profound changes and opportunities with the intelligence and human-centric considerations to the remanufacturing industry. Firstly, the intelligent manufacturing technology has caused the transition from traditional manual operations to digital and automated production, thereby enhancing the efficiency of product disassembly in the remanufacturing process. Specifically, the applications of sensors, robots, and decision-making systems in the remanufacturing process enables more precise and efficient product disassembly. In addition, the integrated application systems such as the Internet of Things, big data, and artificial intelligence has brought new opportunities for digital management and intelligent production to the remanufacturing industry. By considering the real-time monitoring, data analysis, and predictive maintenance, remanufacturing enterprises can better manage production processes by optimizing the production planning and reducing production costs, which improve the efficiency of resource utilization or recycling. Furthermore, intelligent remanufacturing systems based on big data and artificial intelligence can autonomously identify and evaluate the feasibility of EOL product disassembly, while providing more intelligent support for decision-making in the remanufacturing process. The intelligent disassembly technologies have also facilitated the sustainable remanufacturing industry as a key element of the circular economy by extending product lifespans and recycling the resources and materials.

4.1 CPS for disassembly

Cyber-physical system (CPS) is a complex system that connects physical devices to the Internet, enabling them to perform the complex calculations, communication, precise control, remote coordination, and production management by computing and control technologies. This enables real-time perception, information services, and dynamic control of large-scale systems by integrating the virtual network world with the physical world as shown in Figure 4. A new generation of intelligent systems can be built to integrate the computing, communication, and control functions of CPS-based remanufacturing technology [63]. The information physical systems in HRC disassembly have been explored the intelligent disassembly process. Kopacek et al. [64] emphasized the application of intelligent systems to facilitate communication and collaboration of different entities during the disassembly process. Additionally, CPS systems can monitor the entire HRC disassembly operations and generate virtual replicas to optimize the remanufacturing task that can be used to provide the decision-making and improve the efficiency of EOL product disassembly.

The CPS-based disassembly system can be divided into three various layers, including the perception layer, the network layer, and the control layer [65,66], which are interdependent with each other. As shown in Figure 4, the perception layer primarily consists of sensors, controllers, collectors, and other devices, which can be used to collect information and data from the environment and transmit them to the server with the real-time perception of the disassembly process. Nikolakis et al. [67] developed a cyber-physical context-aware system that monitors production lines that facilitates HRC manufacturing process by gathering the real-time data. Filipescu et al. [68] proposed a hybrid assembly/disassembly production line using an

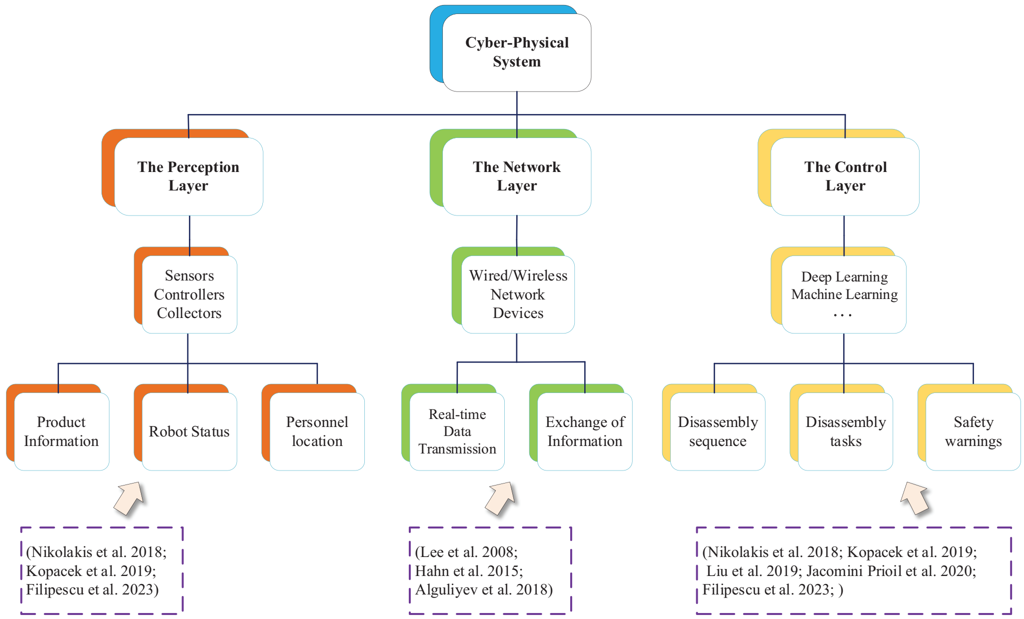

Fig. 4. The different application layers about the disassembly and CPS.

autonomous cyber-physical system (ACPS) for recycling of the EOL products. In the multi-layer architecture, the devices such as monitors are used to implement the functions of the sensing layer. The network layer is used to transfer the real-time monitoring data, which establishes the connection between the information world and the physical world by achieving device interconnection and interoperability. The application control layer primarily focuses on real-time analysis and processing of data by combining the corresponding intelligent algorithms to accomplish the disassembly tasks such as sequence planning optimizations and real-time decision-makings. Liu et al. [53] proposed a novel concept of Cyber-Physical Production Systems (CPPS) into a HRC disassembly framework to acquire the intelligent decision-makings based on reinforcement learning that can be used to achieve efficient collaborative disassembly tasks between humans and robots. Prioli et al. [69] proposed a notion of a cyber-physical information system to develop a training module to enhance the flexibility of disassembly process with co-robots. In addition, it will be meaningful to further explore the research on Human-Cyber-Physical Systems (HCPS), which can be seen as an extension of the information physical system that incorporates human as a key unit into the overall manufacturing or remanufacturing system. This integration primarily aims to leverage the human cognition and their specific actions to optimize the functionality across different application systems [70,71]. Similarly, this HCPS disassembly framework primarily aims to enhance the flexibility of application systems [72] to ensure the safe of HRC disassembly [73] to balance the disassembly cost and time [74].

4.2 IOT for disassembly

Disassembly is a crucial step in the remanufacturing process combining with the emerging technologies like the Internet of Things (IoT). However, it is necessary to overcome certain challenges encountered during the HRC disassembly process of EOL products. Radio Frequency Identification Tags (RFID) are widely used to transfer the device data within the IoT that is capable of being identified through contactless frequency signals. By reviewing the comprehensive literatures, Ferrer et al. [75] extensively discussed the application of RFID technology in remanufacturing processes to demonstrate its potential value that can be used to simplify the EOL product disassembly and enhance the overall efficiency of disassembly process. The application of the IoT combined with HRC disassembly process can be demonstrated as shown in Figure 5.

Before disassembling the EOL products, the pre-processing is required to collect characteristic data such as the size and structure of EOL products for subsequent disassembly planning and decision-making of HRC disassembly processes. The related data can be used to classify the similar EOL products, which can enable the application of a feasible disassembly planning to the EOL products [76]. The IoT can play a significant role in the pre-processing process by recording the data label by the EOL product to obtain basic disassembly information. Wessel et al. [77] proposed a tracking and tracing system based on morphological analysis that provides an automatic identification system based on IoT technology to acquire the product information. Kumar et al. [78] proposed the product information to combine the IoT with artificial intelligence methods, which determine the near-optimal disassembly sequences by validating the collected product information to identify any missing data sets and the operation errors during the disassembly process [79]. The EOL products also require a preliminary assessment of their disassembly condition, while encompassing the health status of EOL products, degree of damage, and other pertinent information [80]. By considering the HRC disassembly of retired EV batteries as an example, it is generally imperative to analyze the characteristics such as remaining battery

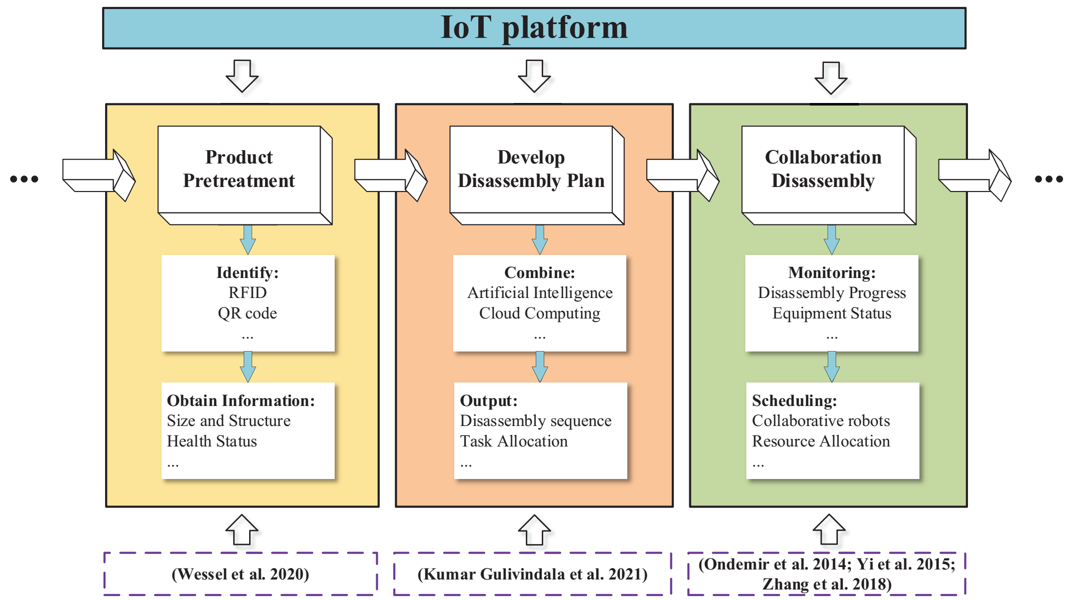

Fig. 5. The framework of the IoT applications about the disassembly process.

capacity and the hazardous substances before disassembly operations [81]. However, it is crucial to ensure the subsequent disassembly safety during the disassembly process. The IoT system can also be utilized for real-time monitoring and scheduling of the collaborative disassembly process. Ondemir et al. [82] proposed a monitoring and data sharing framework for quality management and process optimization in EOL product recycling to improve the efficiency of the recycling processes. Yi et al. [83] demonstrated that IoT technology can be used to explore the recycling of EOL products based on RFID tags to match and track the retired vehicles or its originals. The disassembly status and disassembly processes of EOL products in the disassembly production are also transmitted to the real-time IoT system to support the remote monitoring. Zhang et al. [84] establish an IoT manufacturing environment to achieve real-time production scheduling for the entire remanufacturing system by capturing disassembly information, which provides the experimental verification to improve the effective scheduling.

4.3 Cloud-base remanufacturing system for disassembly

With the development of intelligent manufacturing technologies, cloud technology and other supporting related technologies are gradually being explored in the remanufacturing fields, offering a novel approach for data analysis and information exchange platform in the intelligent production process as shown in Figure 6. However, it is important to enhance the integration of cloud technology, which provides the possibility of HRC disassembly operations in the remanufacturing process. However, the implementation steps of remanufacturing activities can utilize the cloud-based remanufacturing platform to establish a connection between various information systems regarding the remanufacturing process and customer service [3]. Furthermore, it is necessary to combine the cloud-based technologies such as cloud computing and IoT technology that can integrate the useful information or knowledge for future collaborative disassembly technology [78].

Due to the uncertainty of EOL products, the preprocessing of disassembly plays a crucial role in streamlining disassembly operations, while cloud-based remanufacturing systems can also contribute significantly to the process. Xia et al. [85] integrated the Q-learning algorithm with a cloud-based remanufacturing system to propose the diverse disassembly multi-objective optimization. Caterino et al. [3] proposed a cloud remanufacturing system to collaborate with initial information screening for the disassembly process. However, manufacturer-related information can be analyzed by screening the related data from the disassembly planning stage that can be used to reduce planning costs and simplify product disassembly operations. The cloud-based remanufacturing technology can enhance the efficiency of resource scheduling during the disassembly process. Jiang et al. [86] proposed a cloud-based disassembly system that can accomplish the disassembly capabilities of various factories to support different disassembly tasks into disassembly resources. These resources can be allocated and scheduled based on specific disassembly requirements to enable the personalized disassembly services. However, it is necessary to combine the HRC disassembly processes, which can be executed by the disassembly operators with multiple disassembling robots. Each robot can be assigned according to different disassembly operations or tasks, which can allow the real-time scheduling through cloud-based remanufacturing system to meet diverse requirements of EOL product disassembly. Mancusi et al. [87] proposed a cloud computing technology to analyze the data from disassembly process by collecting storing, mining, and transmitting to support the disassembly decision-makings.

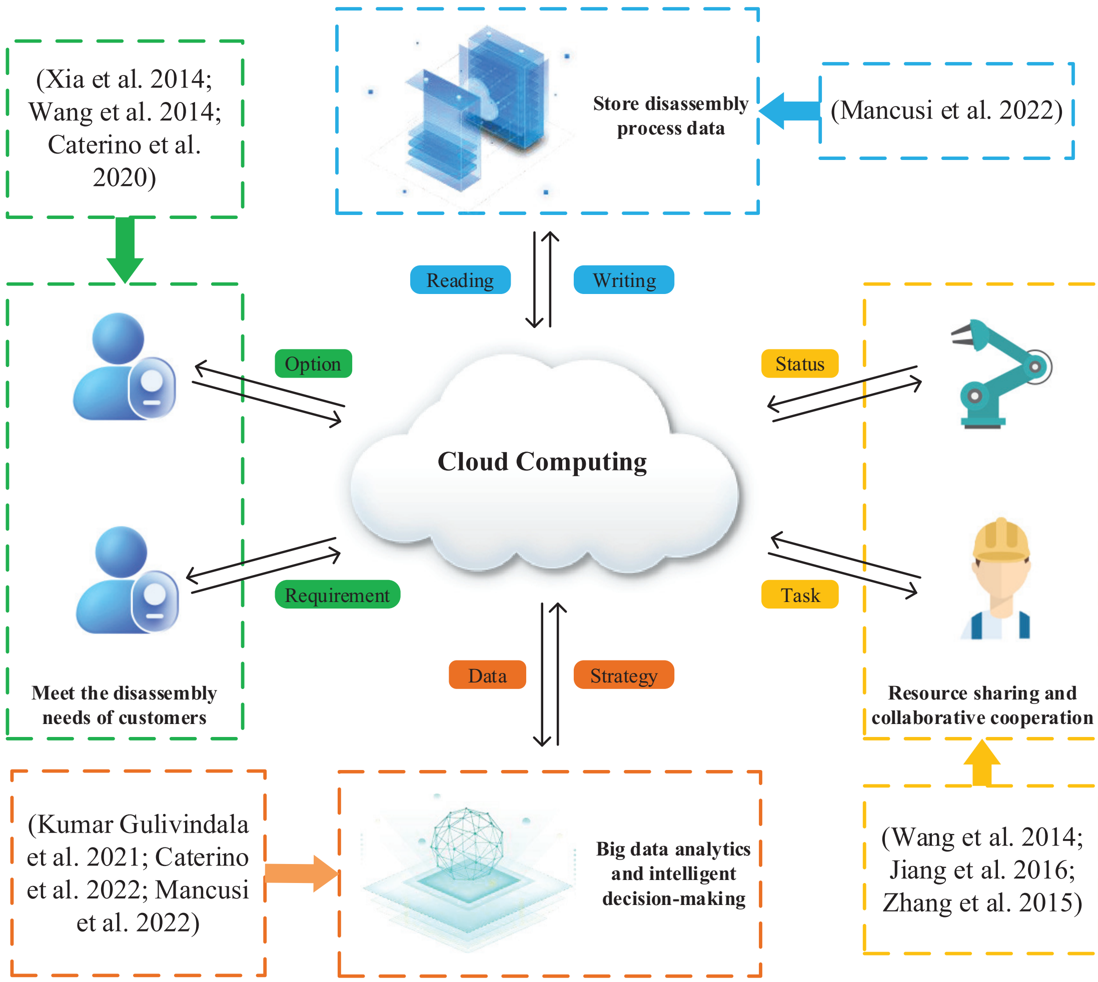

Fig. 6. The fundamental framework of cloud computing technology.

4.4 AI-base remanufacturing system for disassembly

AI-based remanufacturing systems can fulfill various roles to improve the efficiency, safety, and precision of disassembly operations. The subsequent applications of artificial intelligence technology can be divided into disassembly sequence planning, disassembly line balance, and related image recognition and object detection in disassembly process. The disassembly sequence optimization algorithm (i.e., reinforcement learning, heuristic algorithms, etc.) can effectively optimize the disassembly sequence for EOL products while considering multiple disassembly conditions such as product structure, disassembly time and cost as shown in Table 4. However, it is possible to optimize the disassembly operation time, manpower allocation, and resource utilization within the disassembly line. Through computer vision technology, artificial intelligence combined with robot agents can be used to identify various positioning of disassembly objects by tracking their position and operation status. This vision-based information supports robot-assisted disassembly operations by combining computer vision with deep learning technology. Robots can identify obstacles, working station, safety status within the complex environments by avoiding obstacles or hazards during safe disassembly operations.

After reviewing loads of literatures, it has been summarized that genetic algorithms, artificial ant colony optimization, and artificial bee colony algorithms have more attentions on the research of optimization and decision-makings. Furthermore, by analyzing the algorithm characteristics according to different disassembly objects, it is necessary to optimize the specific disassembly sequencing or tasks in the real disassembly operations. Kheder et al. [89] analyzed the probability of disassembly sequence planning, which provides the optimization algorithm to converge on local optimal solutions. With the applications of robots and human operators in the HRC disassembly production line, the effective disassembly task allocation has become crucial for achieving the intelligent and more efficient disassembly. Ranz et al. [120] proposed a reasonable disassembly task allocation to ensure the optimal solution of HRC disassembly by leveraging their respective advantages, thereby improving overall production efficiency. Moreover, by optimization the disassembly strategies, the potential capabilities of both humans and

Table 4. The comparisons between various disassembly optimization methods and disassembly characteristics by reviewing the related literatures.

Disassembly optimization methods	References.	Disassembly sequence optimization	Disassembly line balance	Scenario recognition and object tracking
Genetic Algorithms	Go et al. [88]	√	√	
	Kheder et al. [89]	√		
	Tseng et al. [90]		√	
Ant Colony	Lu et al. [91]	√	√	
	McGovern et al. [92]	√		
	Hu et al. [93]	√	√	
Artificial bee colony	Liu et al. [94]	√	√	
	Hartono et al. [95]		√	
	Kalayci et al. [96]	√		
	Zhang et al. [97]	√	√	
Particle swarm optimization	Pornsing et al. [98]	√	√	
	Tseng et al. [99]	√		
	Tao et al. [100]	√	√	
	Kalayci et al. [101]		√	
Tabu search	Alshibli et al. [102]	√	√	
	Tao et al. [103]		√	
	Kalayci et al. [104]	√	√	
	Liang et al. [105]		√	
Simulated annealing	Xia et al. [106]		√	
	Fang et al. [107]		√	
	Wang et al. [108]		√	
Reinforcement learning	Chu et al. [109]	√		
	Allagui et al. [110]	√		
Convolutional neural networks	Yildiz et al. [111]			√
	Li et al. [112]			√
	Adesso et al. [113]			√
YOLO algorithms	Brogan et al. [114]			√
	Mangold et al. [115]			√
	Zhang et al. [116]			√
Recurrent neural network	Zhang et al. [117]			√
Long short-term memory	Deng et al. [118]			√
	Chen et al. [119]			√

robots can be maximized to provide the greater flexibility and adaptability of the disassembly process. The reasonable disassembly task allocation reduces the risks of HRC disassembly operations while ensuring safety and reliability of the disassembly system. Chen et al. [121] combined genetic algorithms (GA) for real-time disassembly task assignment with the effective requirements reliably. Wu et al. [122] proposed a trust-based dynamic disassembly task assignment method for HRC system to enhance the information interoperability of the disassembly system. Owing to the diversity and complexity of disassembly objects and structures, it is necessary to ensure the effective safety of the actual disassembly during the disassembly process by controlling the optimization algorithm. In addition, it is necessary to enrich the dataset for disassembly processes to enhance algorithm accuracy and generalization capabilities, which can be used to facilitate seamless integration between artificial intelligence technology and remanufacturing systems to improve the efficiency of HRC disassembly systems.

4.5 Digital twin-driven multi-agent disassembly

The implementation of digital twin technology in the semi-automated disassembly process facilitates collaborative disassembly of human operators and robots by generating a

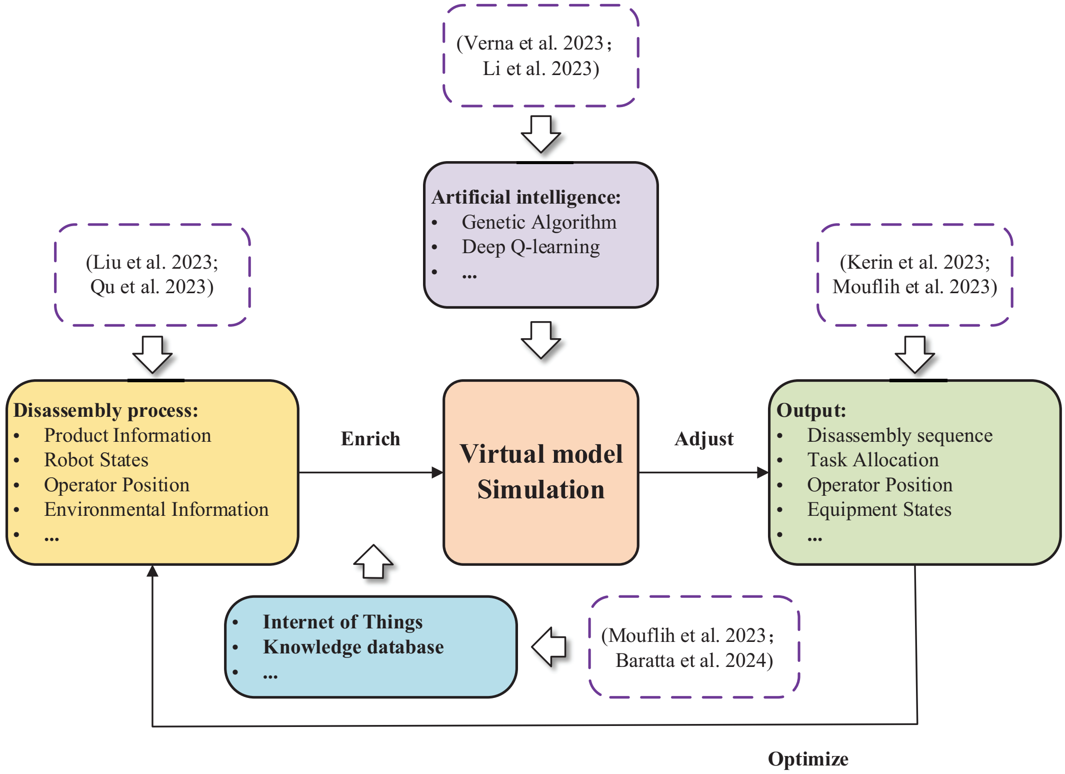

Fig. 7. The application of digital twin-assisted disassembly platform.

virtual replica of the physical system. Through this technology, the data and information can be shared for multi-agents within the virtual environment, which can collaborate effectively to accomplish the intricate disassembly tasks. The disassembly process can be simulated and optimized based on digital twin platform that can enhance the efficient execution of disassembly operations. The overall application mode of digital twin technology in human–robot collaboration disassembly process can be demonstrated as shown in Figure 7. As reviewed many literatures, Mouflih et al. [123] proposed the potential role of digital twins in the disassembly process, which provide the decision-making information during product disassembly to address the efficiency of information exchange. Baratta et al. [124] focused their research on the advantages of digital twins in HRC system, which proposed the robust capabilities of digital twins in simulation testing and optimization of collaboration strategies. However, digital twin technology plays a crucial role in multi-agent collaboration and disassembly processes to offer new possibilities for optimizing the disassembly process.

When multiple agents collaboration accomplishes the disassembly tasks for EOL products, the decision-making of disassembly process might be affected by uncertainties such as the damage of the EOL products. Digital twin technology enables the real-time monitoring and analysis of the EOL product status, while predicting potential issues that may cause during disassembly processes. Furthermore, digital twin technology facilitates the optimization of disassembly planning and control in the disassembly process by simulating various disassembly process to determine the optimal disassembly path. Verna et al. [125] combined digital twin technology with the prediction models to ensure optimal disassembly planning and quality control. Liu et al. [9] analyzed digital twin technology for identifying missing conditions in product disassembly for constructing virtual disassembly spaces and enriching digital twins-based perceptual data transmission. Similarly, the reinforcement learning algorithm can be used to dynamically generate an optimal disassembly sequence while leveraging input data based on digital twin platform to validate and optimize the disassembly strategy generation. Digital twin technology also provided the capabilities of the simulation and analysis in different spatial and temporal scales to simulate and analyze the behavior of systems with the temporal data and information. However, the multi-scale digital twin technology can simulate and optimize the HRC disassembly processes from individual workstations to entire disassembly production lines to improve the efficiency and safety of the disassembly process. Kerin et al. [126] proposed the digital twinning of the EOL products by sensors and IoT technologies to capture product information in real-time or near real-time simulation process, thereby accurately replicating the virtual information of the modeled product. Mouflih et al. [127] considered the digital twin technology of EOL products to support sustainable disassembly decision-makings. Because the virtual model can integrate a large amount of data from EOL product knowledge base, Qu et al. [128] developed a digital twin platform of the HRC disassembly environment to reflect the real-world data into the virtual space for simulation, monitoring, and

Table 5. Representative literatures about the actual industrial disassembly objects.

References.	Disassembly object	Optimization method	Safety constraints
Xiao et al. [8]	Electric Vehicle Battery	Multi-Agent Reinforcement Learning	No
Liu et al. [9]	Camera\Gear pump	Digital twin\Deep Q −learning network	No
Liu et al. [54]	Desktop computer	Convolutional neural network\Long short-term memory network	Yes
Lee et al. [56]	Toy box	Real-time receding horizon sequence planner	Yes
Guo et al. [61]	Hammer drill\ Copying machine\ Radio set	A Pareto improved multi-objective shuffled frog leaping algorithm	No

optimization with intelligent algorithms and machining learning methods to improve the efficiency and flexibility of the disassembly process. Li et al. [129] proposed digital twinning of the entire remanufacturing workshop to create a virtual data to the real workshop, which enables real-time virtual simulation and optimization. The digital twinning technology in multi-agent HRC disassembly is of significant importance for achieving intelligent and efficient disassembly process. However, multi-Agent collaborative modeling and simulation can be accomplished by digital twinning technology to model and simulate multi-agent systems to achieve simulation analysis and optimization of complex disassembly processes. In addition, intelligent decision support systems can develop the intelligent decision support systems based on digital twinning technology for the decision-makings of multi-agent HRC disassembly processes. Furthermore, intelligent monitoring and prediction can be constructed by digital twinning technology to achieve real-time monitoring and prediction of multi-agent HRC disassembly processes. Finally, intelligent optimization and resource allocation can be accomplished by digital twinning technology to intelligently optimize the workflow and resource allocation of multi-agent HRC disassembly to achieve optimal disassembly process.

5 Actual industrial disassembly applications

By considering the varying levels of difficulty in the actual industrial disassembly processes, it is necessary to collect the engineering practices from representative literatures as shown in Table 5. In terms of engineering applications, there is relatively more research focused on the disassembly of retired lithium-ion EV batteries. Due to the rapid growth of electric vehicles in recent years, it is imperative to find out the solutions for the environmental pollution caused by recycling the lithium-ion batteries and its disassembly production [130]. In addition, we specifically investigated whether these optimization methods included safety constraints, and over 50% of the studies considered this aspect. However, some researches only focused on improving efficiency and flexibility while neglecting the safety aspect. Safety issues are crucial in industrial applications, and determine the future massive applications. Therefore, it is necessary to prioritize both efficiency improvement and safety considerations in human–robot collaboration disassembly to better practical industrial disassembly.

In the case of human–robot collaboration disassembly of EV batteries, the actions of both human operators and robots can be considered as the smallest unit of action related to the execution of a disassembly task. The disassembly workstation can be conceptualized as a system with the human operator and the robot [131]. Based on observed EV battery structure, we can deal with specific intelligent optimization techniques, the real-time optimal or near-optimal disassembly strategies and task allocation. With further development of HRC disassembly technology, its actual industrial application will expand to more possible industrial application fields. For example, the disassembly and recycling of automotive engine components can be explored by disassembling its valuable components in the engine, such as crankshafts, connecting rods, and gears, are typically high-quality metal products. Similarly, the disassembled components can allow for the recovery and reuse of valuable materials, reducing resource waste and environmental burden, which also contributes to the promotion of a circular manufacturing economy.

6 Discussion

Through analyzing the existing scientific technologies, the artificial intelligence and digital twin technology in the human–robot collaboration (HRC) disassembly process is gradually paid more attention to consider the uncertainty of EOL products. Subsequently, robot-centered remanufacturing systems can accomplish the higher efficient disassembly in the disassembly process. However, the disassembly method has brought about new issues such as disassembly sequence planning, disassembly task allocation, and collaborative safety. Furthermore, the applications of advanced remanufacturing technologies (i.e., cyber-physical systems, Internet of Things, cloud computing, artificial intelligence, and digital twin technology) have more feasibility when facing with HRC disassembly.

However, multi-agent human and robot collaboration in the context of disassembly has huge potentials to deal with the complex disassembly. The collaborative work with multiple robots can involve mutual cooperation to jointly achieve a disassembly goal or mutual assistance in different manufacturing processes. Through multi-robot collaborative disassembly, the flexibility and efficiency of the disassembly production line can be further enhanced to reduce the workload of manual operations.

- Task allocation and planning: it is necessary to allocate disassembly tasks to different robots, maximizing their capabilities and resources. Task allocation and planning algorithms should consider workload balancing, task interdependencies, and disassembly strategies for HRC. Similarly, IoT and cloud computing technologies can be utilized to dynamically allocate and optimize disassembly tasks through digital twin platform. Real-time data collected by physical devices and sensors can be analyzed by using cloud computing to provide optimal disassembly task allocation strategies.
- Collaborative decision-making and control: it is necessary to achieve collaborative decision-making and control between human workers and multiple robots, ensuring efficiency and safety in the collaborative disassembly process. By considering the AI techniques, such as deep learning and reinforcement learning algorithms, collaborative decision-making and control between multiple robots and human workers should be further explored. By analyzing large-scale data and real-time feedback data, intelligent HRC disassembly can be enhanced, resulting in efficient collaborative decision-making and control.
- Performance evaluation and optimization: it is necessary to evaluate the performance of multi-agent HRC collaborative disassembly through the use of defined performance metrics, simulation experiments, and data analysis techniques. Real-time optimization strategies can be implemented to enhance the efficiency and quality of disassembly objects. By combining with digital twin and big data analytics, it will be a trend to integrate virtual model simulations, analysis of large-scale data, extraction of valuable performance indicators, and subsequent multi-objective optimization, etc.

Meanwhile, the implementation of digital twinning technology in existing industrial disassembly lines may not be widespread. With the increasing number of End-of-Life (EOL) products, the efficient requirements of HRC disassembly will become increasingly stringent. As digital twinning technology continues to integrate deeply into intelligent disassembly, its application in future HRC disassembly will become more widespread, leading to many potential research directions, including but not limited to:

- The optimization of the digital twinning technology can achieve more accurate simulation and prediction of HRC disassembly processes. The construction of digital twinning platform needs to consider complex characteristics such as multi-scale and multi-physics simulations to reflect the models the accurate characteristics and behavior of the disassembled objects or disassembly production lines. By optimizing the established digital twinning platform, the precise simulation and prediction of the disassembly process can be carried out to enhance the accuracy of the output results. By focusing on the existing HRC disassembly-related field, human operator behavior and emergency response measures after human–robot collisions can be efficiently predicted to ensure the safety of the entire disassembly process. Through the simulation of virtual human behavior using digital twinning technology, the effective prediction of human behavior can be achieved to avoid human–robot collisions. If a collision cannot be avoided, the simulation can be used to find out the optimal robot working feedbacks (such as returning to the original position, moving away from the operator, or shutting down directly) to achieve an effective balance between safety and efficiency.
- However, it is necessary to explore the integration of digital twinning technology with artificial intelligence to achieve the adaptive and intelligent disassembly decision-makings. The intelligent decision support systems within digital twinning technology can is gradually developing intelligent decision-making capabilities for different disassembly scenarios through the continuous optimizations of disassembly tasks. Furthermore, the combination of digital twinning technology with artificial intelligence can also facilitate the prediction and early warnings of potential disassembly issues during the disassembly process. By integrating the risk prediction and fault diagnosis modules into digital twinning platform, the potential safety hazards can be dynamically monitored in the real-time intelligent disassembly system that can provide the timely safety precautions to handle the recommendations for disassembly operators.
- In addition, the real-time monitoring and feedback systems of digital twinning technology in HRC disassembly processes can be used to enhance the efficiency and accuracy of the disassembly operations by the real-time calibration and comparison of the original model. The actual data can enable the dynamic monitoring and real-time control of collaborative disassembly processes, which can facilitate the timely detection of anomalies during the disassembly process. Moreover, by feedbacking the actual data to the digital twinning platform, it can analyze and evaluate the effectiveness and risks of the current disassembly method, as well as potential optimization opportunities. Additionally, digital twinning technology can be combined with expert systems and knowledge graphs to achieve intelligent analysis and diagnostics of real-time monitoring data. By considering multi-domain knowledge and experiential rules embedded in the complex disassembly model, the real-time data can be intelligently analyzed and assessed to provide the relevant optimization recommendation.
- The application of digital twinning technology with other intelligent technologies (i.e.: Internet of Things (IoT), cloud computing, etc.) can be used to promote the innovation of the intelligent disassembly. Through the real-time data collected by IoT devices, the digital twinning platform can capture the real-time physical and virtual disassembly data by the collection methods, facilitating dynamic monitoring and intelligent decision-making in the disassembly process. Combined with cloud computing technology, it can enable the cross-regional collaboration, the large-scale data processing, and the real-time data feedback. The application of digital twinning technology will further push the development

of intelligent disassembly to achieve the intelligent, efficient, and sustainable disassembly processes that can provide the better technological support for the industrial disassembly productions.

By completely reviewing the optimizing HRC disassembly mentioned in the paper, the general method provided in the disassembly-related researches may not be applicable to the specific disassembly lines, but these current challenges will be given attention on the future researches to push the development of the flexible and intelligent disassembly process in the remanufacturing fields.

7 Conclusion

In this paper, the comprehensive reviews on human–robot collaborative (HRC) disassembly will be a key focus of future research. The integration of intelligent disassembly technologies has been widely used to significantly improve the efficient of disassembly process, which assists robotic systems in achieving more intelligent and accurate disassembly decisions and operations. Additionally, the comprehensive literatures about HRC disassembly technology has been discussed for the functionality and applicability of robot disassembly, which provides the diversified solutions for disassembly tasks in different complex scenarios. Simultaneously, the comprehensive disassembly technologies have been deeply explored to ensure the integrated safety to reduce the unforeseen risks during the disassembly process. By considering HRC disassembly line based on various optimization methods, digital twin technology in collaborative disassembly can be effectively incorporated into HRC disassembly to enhance the efficiency and safety of the disassembly process.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

Data will be made available on request.

Author contribution statement

Jinhua Xiao: Conceptualization, Methodology, Investigation, Formal analysis, Software, Writing – Original Draft, Writing – Review & Editing. **Kaile Huang**: Data curation, Visualizations, Writing – Original Draft.

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