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Review of Research on Human-Machine Collaboration in Disassembly Line Balancing Problem

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ABSTRACT

This paper aims to explore the research on the human-machine collaboration in the disassembly line balancing problem, in response to the importance of dismantling and reusing waste products. Human-machine collaboration in disassembly, as a method combining human intelligence with machine power, has the potential to enhance disassembly efficiency, reduce resource wastage, and minimize human exposure to hazards. However, due to the NP-hard nature of this problem, traditional exact algorithms perform poorly when facing large-scale and complex problems. Therefore, this paper explores the application of intelligent algorithms such as genetic algorithms, wolf pack algorithms, etc., and proposes novel and efficient solutions to the human-machine collaboration in disassembly line balancing problem. Additionally, to address the challenge of the large-scale problem state space, this paper also discusses the potential application of emerging technologies such as reinforcement learning. Through these studies, this review aims to promote the development of the remanufacturing industry and facilitate resource utilization and environmental protection.

KEYWORDS

Human-machine collaboration; Disassembly line balancing; Solution methods

1. INTRODUCTION

With the advancement of China's transition from the "Made in China 2025" strategy to the "Smart Manufacturing in China 2035" strategy, the production level and comprehensive national strength of China have gradually increased, bringing about the issue of secondary resource recycling. Specifically, on one hand, the disposal of waste products containing heavy metals and other hazardous substances directly contributes to severe environmental pollution; on the other hand, waste products contain valuable components that can be reused, and direct disposal leads to significant resource wastage [1]. Therefore, in order to minimize the negative impact of waste products on the ecological environment and resource utilization, it is necessary to promptly and effectively recycle and process waste products. Currently, China's utilization rate of recycled resources is relatively low, and the government has been actively and continuously issuing policies to guide its development. As early as January 2015, the Ministry of Commerce issued the "Medium and Long-Term Plan for the Construction of Recycling Resource Recovery System (2015-2020)", proposing to cultivate around 100 backbone enterprises for recycling resources and achieve a total recycling volume of around 220 million tons. The "14th Five-Year Plan for Circular Economy Development" released in 2021 pointed out that the development of the circular economy is of great significance for improving resource utilization efficiency, promoting the level of recycled resource utilization, and driving high-quality economic and social development. In pursuit of economic benefits and achieving sustainable development, an increasing number of enterprises have begun to pay attention to reverse logistics, which involves the logistics of returning goods from consumers to production enterprises.

The current literature on reverse logistics regards disassembly/remanufacturing as the first step in the reverse logistics field [2]. Remanufacturing is an essential approach to effectively recycle and reuse waste products, thereby promoting resource conservation and environmental protection. It aims to transform waste products into new products through a series of operations such as disassembly, processing, and reassembly. Research indicates that remanufactured products can achieve cost savings of 50%, energy savings of 60%, and material savings of 70% compared to new products.Disassembly is the primary link in the remanufacturing process, aiming to execute a series of disassembly operations to separate and obtain valuable parts or components from waste products, greatly affecting the operational efficiency of remanufacturing systems and the economic benefits of reverse supply chains [3]. In recent years, with the continuous advancement of technology and industry, the manufacturing and application of large-scale products have shown a thriving trend. These complex products, such as aircraft, industrial equipment, automobiles, and electronic products, have highly intricate structures and components, containing a large number of recyclable parts. Effectively disassembling and recycling these components and materials has become an urgent problem to address. In the process of dismantling large-scale waste products, there are various disassembly solutions, and quickly identifying satisfactory disassembly solutions is one of the pressing issues facing disassembly enterprises.

In order to improve disassembly efficiency and effectiveness, and to promote the safe and efficient operation of remanufacturing systems, the disassembly optimization problem has been extensively studied by academia and industry. The objective is to formulate disassembly schemes under the premise of satisfying internal structural constraints of products to achieve optimal decision-making objectives.

Disassembly operations can be carried out at individual workstations, disassembly units, or disassembly lines. While individual workstations and disassembly units offer more flexibility, the highest productivity is provided by disassembly lines. As the scale and complexity of products increase, utilizing disassembly lines for product disassembly becomes the optimal choice for disassembling large-scale products [4]. Moreover, disassembly operations can be conducted by both humans and machines. Compared to independent robot disassembly and manual disassembly, human-machine collaborative disassembly has the advantages of efficient and stable processes, as well as flexible and versatile procedures. The disassembly line balancing problem can be defined as the allocation of disassembly tasks to ordered workstation sequences that satisfy all priority relationships and optimization performance metrics [5]. Disassembly lines are primarily composed of products to be disassembled, workstations, disassembly tools, personnel, transmission devices, etc. Finding the optimal solution to the disassembly line balancing problem is typically difficult, as the problem complexity is NP-hard [6]. With the increase in problem scale and complexity, researchers have focused on developing heuristic methods to address the challenges. Therefore, a series of heuristic and metaheuristic methods have been developed to find the best or near-optimal solutions for the disassembly line problem.

2. RESEARCH OBJECTIVES AND SIGNIFICANCE

The continuous upgrading of products and the end of their service life lead to challenges in disassembly and processing. Concurrently, human-machine collaborative disassembly integrates human intelligence and machine power, which can enhance the efficiency of the disassembly process. Delegating hazardous tasks to machines reduces direct human exposure to dangerous environments, thus safeguarding human safety and health. Therefore, researching the human-machine disassembly problem holds significant research background and value. However, due to the problem's NP-hard complexity, solving it becomes increasingly difficult with the escalation of problem scale and complexity. Some studies on disassembly line balancing problems employ precise algorithms to identify optimal sequences for discarded products with a small number of components [7]. Nevertheless, as the number of components in discarded products increases, the problem space expands dramatically. Researchers quickly realized that precise algorithms are inadequate for addressing larger problem instances. For any given product with K components, the solution space for the balancing problem comprises K! different task sequences, including feasible and infeasible ones. With the growing attention to disassembly line balancing issues, various algorithms have been applied to address them. Currently, intelligent algorithms such as genetic algorithms, wolf pack algorithms, cuckoo search algorithms, among others, are commonly employed.

In summary, the research on human-machine collaborative disassembly line balancing problem holds significant academic significance and practical value. With the increasing importance of handling waste products, optimizing the disassembly process by combining human intelligence with machine power will drive the development of the remanufacturing industry. However, due to the complexity and NP-hard nature of the problem, the limitations of traditional precise algorithms become evident, necessitating the utilization of intelligent algorithms such as genetic algorithms, wolf pack algorithms, among others, to address larger scale and complexity issues. Furthermore, research on human-machine collaborative disassembly contributes to optimizing resource utilization and environmental protection.

3. REVIEW OF DOMESTIC AND INTERNATIONAL RESEARCH

Disassembly line is an effective approach for efficient disassembly of waste products. In order to further improve disassembly efficiency, numerous scholars at home and abroad have conducted extensive research on Disassembly Line Balancing Problem (DLBP). DLBP aims to investigate how to obtain a series of disassembly tasks and determine their execution order as well as the allocation of disassembly tasks on workstations under the premise of satisfying the priority relationships of disassembly tasks and the disassembly production pace, thereby achieving optimal disassembly objectives such as disassembly profit and disassembly time. The following mainly introduces DLBP from two aspects: disassembly mode and solution methods.

3.1. Review of Research on Different Disassembly Modes

Product disassembly is the process of sequentially releasing the constraints between parts and products, and removing the parts. The disassembly sequence plays a guiding role in the disassembly process. Robot disassembly has higher efficiency and stability compared to manual disassembly, but lacks flexibility for scrapped products with different component structures. In this case, the advantages of human-robot collaboration disassembly are obvious. Human-robot collaboration disassembly combines the characteristics of industrial robot disassembly and manual disassembly, with higher flexibility and disassembly efficiency compared to manual disassembly and robot disassembly. The research status of disassembly sequence planning methods for three modes of disassembly, namely manual disassembly, robot automated disassembly, and human-robot collaboration disassembly, will be discussed separately.

Existing research outcomes primarily focus on the manual disassembly process. The primary step in disassembly sequence planning is the modeling of disassembly information, wherein the priority constraints between components are transformed into a mathematical model suitable for computer processing to ensure the feasibility of the disassembly sequence. Zhang et al. extended the disassembly mixed graph and defined connection elements composed of connected and connecting components. Guo et al. [8] expanded the basic pentuple of Petri nets, adding descriptions of disassembly costs, recycling/reuse value, and resource constraints for each transition. Considering the time cost of solving the optimal disassembly sequence, intelligent optimization algorithms have received broader research attention compared to exact algorithms. The key to using intelligent optimization algorithms for disassembly sequence planning lies in improving the process of the original algorithm to adapt to the discrete nature of the disassembly sequence. Guo et al. [8] proposed two improved decentralized search algorithms with different combination optimization operators for the selective disassembly sequence planning problem of large products under multiple resource constraints. Zhang et al. [9] applied the artificial fish swarm algorithm to the multi-objective fuzzy disassembly line balancing problem. Tian et al. [10] combined fuzzy simulation with artificial bee colony algorithm to solve the disassembly sequence planning problem in uncertain environments. They improved the selection mechanism of forager bees in the artificial bee colony algorithm by randomly selecting two food sources, selecting the better one based on a competition mechanism for neighborhood search, thereby shortening the time for calculating selection probabilities based on sorting food source quality.

Liu et al. [11] pointed out that sequence planning methods for manual disassembly are not applicable to robotized automated disassembly processes. Due to the different movement characteristics between robots and humans, when the robot end effector moves between two disassembly points, obstacle avoidance along the product contour should be considered. Therefore, the disassembly time should include the movement time determined by the product contour and the robot end effector speed. Torres et al. [12] studied task planning in robot collaborative disassembly systems, categorizing disassembly tasks into collaborative types requiring multiple robot cooperation and parallel types that a single robot can complete. The system dynamically detects each robot's workspace and tool availability, seeking the optimal allocation for each task using decision trees. Elsayed et al. [13] developed automated selective disassembly units based on industrial robots, machine vision, distance sensors, and image segmentation algorithms. Real-time selective disassembly sequence planning is performed using a genetic algorithm based on detected product disassembly states. Vongbunyong et al. [14] investigated the application of cognitive robots in automated disassembly. They proposed an automated disassembly system integrating four cognitive functions: reasoning, execution monitoring, learning, and correction. This system dynamically plans disassembly operations based on actual disassembly states without requiring prior knowledge about the discarded products.

Research on human-robot collaboration in disassembly sequence planning is relatively scarce, with current studies mainly focusing on task allocation in human-robot collaboration. Tsarouchi et al. [15] provided a design approach for collaborative workspace and task planning in human-robot collaboration, further detailing the design of positions and equipment for humans and robots within the workspace. Ranz et al. [16] described the capabilities of humans and robots and categorized tasks into immutable and mutable tasks. They evaluated task allocation based on time, additional costs, and quality as capability assessment criteria. Guo et al. [17] investigated the application of intelligent planning methods in human-robot collaborative assembly sequence and task planning. They proposed a two-level planning approach, where in the first level, assembly direction and time are optimized based on ant colony algorithm as heuristic information. In the second level planning, considering the results of the first-level planning, human-robot interaction information is taken into account for serial sequence planning and assembly task allocation.

3.2. Review of Disassembly Line Balancing Solution Methods

Numerous methods have been designed and proposed to address the Disassembly Line Balancing Problem (DLBP), mainly categorized into exact solution methods, heuristic methods, and intelligent optimization algorithms. DLBP was initially proposed by Gungor and Gupta, who used priority functions in heuristic methods to solve simple DLBP problems [5]. Avikal et al. employed a heuristic algorithm to solve the DLBP problem, but it was only applicable to solving small-scale problems [18]; Altekin and Akkan optimized DLBP using linear programming, but they could not solve large-scale problems [19]. Due to their excellent solving performance, i.e., being able to find satisfactory solutions to problems within a reasonable time frame, intelligent optimization algorithms have been widely successfully applied to solve disassembly optimization problems. Below is a literature review of several common intelligent optimization methods for solving disassembly optimization problems.

Tseng et al. [20], based on a comparison between Kongar and Gupta's genetic algorithm and Dijkstra's algorithm, proposed a new block-based disassembly sequence planning genetic algorithm, which can effectively address the disassembly sequencing problem. Lee et al. [21] introduced an interactive genetic algorithm to solve the disassembly sequence planning problem, demonstrating its effectiveness on small to medium-sized disassembly products. Li et al. developed a multi-objective immune mechanism cooperative genetic algorithm based on the Pareto solution set to address the problem of uneven workload distribution on disassembly lines. This approach was validated on small-scale problems with 10 components and large-scale problems with 52 components, showcasing its effectiveness and superiority.

Tian et al. [10] proposed a hybrid intelligent algorithm that integrates fuzzy simulation and artificial bee colony to solve the disassembly sequence planning problem considering uncertain component quality and different disassembly operational costs. Wang et al. [22] introduced a discrete artificial bee colony algorithm based on problem characteristics, focusing on the new problem of parallel disassembly sequence planning for robotic disassembly of discarded products. Xu Chengcheng established a multi-objective mathematical model based on human-machine collaboration to maximize profit, minimize energy consumption, and minimize disassembly difficulty. They proposed an improved artificial bee colony algorithm to solve this problem.

Tseng et al. [23] proposed a hybrid bidirectional ant colony optimization algorithm and compared it with four related algorithms. The results showed that the hybrid bidirectional ant colony optimization algorithm provided solutions superior to other ant algorithms. Feng et al. [24] introduced an improved multi-objective ant colony algorithm to derive the optimal objective disassembly sequence. Zhang Zeqiang et al. addressed the shortcomings of traditional methods in solving multi-objective U-shaped disassembly line balancing problems and proposed a multi-objective ant colony genetic algorithm based on Pareto solution set.

Xia et al. [25] proposed an adaptive hybrid particle swarm genetic algorithm to solve the sequence-dependent stochastic mixed-model disassembly line balancing problem model. Xiao et al. [26] introduced an entropy-based adaptive hybrid particle swarm optimization algorithm, which utilized entropy to measure the change trend of population diversity and employed dimension learning, crossover, and mutation operators to enhance the probability of generating feasible disassembly solutions. Fang et al. aimed to enhance the computational capability of particle swarm optimization algorithms in solving complex disassembly line balancing problems and proposed an improved particle swarm optimization algorithm.

Tuncel et al. [27] utilized Monte Carlo-based reinforcement learning techniques to address the disassembly line balancing problem, with research findings indicating that reinforcement learning-based methods could effectively perform even on complex large-scale problems within reasonable computational time. Mete and Serin [28] proposed a reinforcement learning approach to tackle the disassembly line balancing problem, aiming to minimize the number of workstations within a given cycle time. Liu et al. [29] employed an improved Q-learning algorithm based on reinforcement learning to address the bilateral disassembly line balancing problem, with the objective of minimizing the total disassembly time.

4. SUMMARY

Currently, optimization of disassembly line balancing in remanufacturing mainly focuses on traditional manual disassembly lines and a few robotic disassembly lines, with limited mention of optimization for human-robot collaborative disassembly lines. However, there has been significant progress in the application of human-robot collaboration in other manufacturing fields. Human-robot collaborative disassembly can achieve better disassembly balance by coordinating the efforts of operators and industrial robots to complete disassembly tasks. Existing research on disassembly optimization primarily employs classical intelligent optimization algorithms such as genetic algorithms and artificial bee colony algorithms to solve disassembly optimization problems. Each algorithm has its own advantages and disadvantages. For instance, genetic algorithms have strong global search capabilities but weak local search capabilities and slow convergence speed. The artificial bee colony algorithm balances global and local search capabilities well but requires complex parameter settings. Ant colony algorithms exhibit robustness and good optimization capabilities but weak local search capabilities, making them prone to local optima. Particle swarm optimization algorithms have fast convergence speed but are prone to premature convergence and poor population diversity. A limited number of studies have begun to use reinforcement learning to solve disassembly line problems. However, when the problem state or space is large-scale, table-based reinforcement learning methods cannot adequately represent these states. Therefore, to further optimize the solution of disassembly optimization problems, it is necessary to consider designing novel and efficient intelligent optimization algorithms and other solution techniques.

REFERENCES

[1] Guo X, Liu S, Zhou M, et al. Dual-Objective Program and Scatter Search for the Optimization of Disassembly Sequences Subject to Multiresource Constraints [J]. IEEE Transactions on Automation Science and Engineering, 2018, 15(3): 1091-1103.

[2] Reveliotis S A. Uncertainty management in optimal disassembly planning through learning-based strategies [J]. IIE Transactions, 2007, 39(6): 645-658.

[3] Liang P, Fu Y, Ni S, et al. Modeling and optimization for noise-aversion and energy-awareness disassembly sequence planning problems in reverse supply chain [J]. Environmental Science and Pollution Research, 2021.

[4] Kalayci C B, Gupta S M. A tabu search algorithm for balancing a sequence-dependent disassembly line [J]. Production Planning & Control, 2014, 25(2): 149-160.

[5] Gungor A, Gupta S M. Disassembly line in product recovery [J]. International Journal of Production Research, 2002, 40(11): 2569-2589.

[6] Mete S, Cil Z A, Agpak K, et al. A solution approach based on beam search algorithm for disassembly line balancing problem [J]. Journal of Manufacturing Systems, 2016, 41: 188-200.

[7] Lambert A J D. Optimizing disassembly processes subjected to sequence-dependent cost [J]. Computers & Operations Research, 2007, 34(2): 536-551.

[8] Guo X, Liu S, Zhou M, et al. Disassembly Sequence Optimization for Large-Scale Products With Multiresource Constraints Using Scatter Search and Petri Nets [J]. IEEE Transactions on Cybernetics, 2016, 46(11): 2435-2446.

[9] Zhang Z, Wang K, Zhu L, et al. A Pareto improved artificial fish swarm algorithm for solving a multi-objective fuzzy disassembly line balancing problem [J]. Expert Systems with Applications, 2017, 86: 165-176.

[10] [10] Tian G, Zhou M, Li P. Disassembly Sequence Planning Considering Fuzzy Component Quality and Varying Operational Cost [J]. IEEE Transactions on Automation Science and Engineering, 2018, 15(2): 748-760.

[11] Liu J, Zhou Z, Duc Truong P, et al. Robotic disassembly sequence planning using enhanced discrete bees algorithm in remanufacturing [J]. International Journal of Production Research, 2018, 56(9): 3134-3151.

[12] Torres F, Puente S, Diaz C. Automatic cooperative disassembly robotic system: Task planner to distribute tasks among robots [J]. Control Engineering Practice, 2009, 17(1): 112-121.

[13] ElSayed A, Kongar E, Gupta S M, et al. A Robotic-Driven Disassembly Sequence Generator for End-Of-Life Electronic Products [J]. Journal of Intelligent & Robotic Systems, 2012, 68(1): 43-52.

[14] Vongbunyong S, Kara S, Pagnucco M. Learning and revision in cognitive robotics disassembly automation [J]. Robotics and Computer-Integrated Manufacturing, 2015, 34: 79-94.

[15] Tsarouchi P, Michalos G, Makris S, et al. On a human-robot workplace design and task allocation system [J]. International Journal of Computer Integrated Manufacturing, 2017, 30(12): 1272-1279.

[16] Ranz F, Hummel V, Sihn W. Capability-based task allocation in human-robot collaboration; proceedings of the 7th Conference on Learning Factories (CLF), Darmstadt, GERMANY, F 2017Apr 04-05, 2017 [C]. 2017.

[17] Guo J, Bai C, Chen C. Sequence planning for human and robot cooperative assembly of large space truss structures [J]. Aircraft Engineering and Aerospace Technology, 2017, 89(6): 804-808.

[18] Avikal S, Mishra P K, Jain R. A Fuzzy AHP and PROMETHEE method-based heuristic for disassembly line balancing problems [J]. International Journal of Production Research, 2014, 52(5): 1306-1317.

[19] Altekin F T, Akkan C. Task-failure-driven rebalancing of disassembly lines [J]. International Journal of Production Research, 2012, 50(18): 4955-4976.

[20] Tseng H-E, Chang C-C, Lee S-C, et al. A Block-based genetic algorithm for disassembly sequence planning [J]. Expert Systems with Applications, 2018, 96: 492-505.

[21] Lee S-C, Tseng H-E, Chang C-C, et al. Applying Interactive Genetic Algorithms to Disassembly Sequence Planning [J]. International Journal of Precision Engineering and Manufacturing, 2020, 21(4): 663-679.

[22] Wang K, Gao L, Li X, et al. Energy-Efficient Robotic Parallel Disassembly Sequence Planning for End-of-Life Products [J]. IEEE Transactions on Automation Science and Engineering, 2022, 19(2): 1277-1285.

[23] Tseng H-E, Chang C-C, Lee S-C, et al. Hybrid bidirectional ant colony optimization (hybrid BACO): An algorithm for disassembly sequence planning [J]. Engineering Applications of Artificial Intelligence, 2019, 83: 45-56.

[24] Feng Y, Zhou M, Tian G, et al. Target Disassembly Sequencing and Scheme Evaluation for CNC Machine Tools Using Improved Multiobjective Ant Colony Algorithm and Fuzzy Integral [J]. IEEE Transactions on Systems Man Cybernetics-Systems, 2019, 49(12): 2438-2451.

[25] Xia X, Liu W, Zhang Z, et al. Partial Disassembly Line Balancing Problem Analysis Based on Sequence-Dependent Stochastic Mixed-Flow [J]. Journal of Computing and Information Science in Engineering, 2020, 20(6).

[26] Xiao S, Wang Y, Yu H, et al. An Entropy-Based Adaptive Hybrid Particle Swarm Optimization for Disassembly Line Balancing Problems [J]. Entropy, 2017, 19(11).

[27] Tuncel E, Zeid A, Kamarthi S. Solving large scale disassembly line balancing problem with uncertainty using reinforcement learning [J]. Journal of Intelligent Manufacturing, 2014, 25(4): 647-659.

[28] Mete S, Serin F. A Reinforcement Learning Approach for Disassembly Line Balancing Problem [Z]. 2021 International Conference on Information Technology (ICIT). 2021: 424-427.10.1109/icit52682.2021.9491689

[29] Liu Y, Zhou M, Guo X. An Improved Q-Learning Algorithm for Human-robot Collaboration Two-sided Disassembly Line Balancing Problems [Z]. 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC). 2022: 568-573.10.1109/smc53654.2022.9945263