

Review

# Disassembly Line Balancing for Sustainable Manufacturing: A Systematic Review of Models, Algorithms, and Future Directions

Jiaju Peng<sup>1</sup>, Guangdong Tian<sup>1,\*</sup>, Duc Truong Pham<sup>2</sup>, Hao Huang<sup>1</sup>, Hongbin Chi<sup>1</sup> and Songang Zhang<sup>1</sup>

<sup>1</sup> School of Mechanical-Electronic and Vehicle Engineering, Beijing University of Civil Engineering and Architecture, Beijing 100044, China

<sup>2</sup> Department of Mechanical Engineering, University of Birmingham, Birmingham B15 2TT, UK

\* Correspondence: [tiangd2013@163.com](mailto:tiangd2013@163.com)

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**Abstract:** Disassembly line balancing (DLB) has become an important technology for sustainable manufacturing, implementation of circular economy and recovery of end-of-life (EOL) products. With the increase in the complexity of waste electrical and electronic equipment, electric vehicle batteries and human-robot cooperative disassembly systems, DLB research has progressed from conventional deterministic optimization towards intelligent, uncertainty aware and sustainability oriented decision-making. In this paper, we present a detailed and thorough survey of recent advancements in DLB by analysing 135 representative papers published from 2003 to 2025, where about 80% were published after 2020. A Grounded Theory based literature review method was applied to systematically classify the existing research according to the disassembly representation methods, optimization objectives, mathematical models, uncertainty modelling strategies and solution algorithms. Special emphasis was put on the development of intelligent optimization techniques such as exact algorithms, heuristic methods, swarm intelligence, hybrid meta-heuristics, stochastic and fuzzy programming and recent reinforcement learning approaches. Additionally, this review suggests an integrated analytical framework which reveals the connections between optimization objectives, modelling paradigms and algorithmic developments, providing a better understanding of the technological progress of DLB. According to a comprehensive evaluation of the current achievements and the remaining shortcomings, six promising research fields are identified, including digital twin supported adaptive disassembly, intelligent decision-making assisted by large language models, multi-agent collaborative optimisation, human-robot cooperation, carbon aware circular manufacturing and data driven autonomous disassembly systems. This review not only summarises the present status of DLB research but also establishes a systematic guide for the development of next generation intelligent disassembly systems towards Industry 5.0 and sustainable manufacturing.

**Keywords:** disassembly line balancing; intelligent optimization; sustainable manufacturing; human-robot collaboration; circular economy



## 1. Introduction

With the rapid development of the global economy and a greatly increasing population, consumer demand for goods and services keeps increasing. It causes resource overexploitation and environmental deterioration [1,2]. People are casting huge wastes and waste products into environment, such as air pollution, water pollution and soil pollution. Global resource consumption was far beyond the natural renewal level and the problem of global resource deprivation emerges [3,4]. To meet the requirements of future generations, people pay much more attention to sustainability [5]. Product recycling concerns people more and more seriously with increasing severity of environmental problems, increasing pressure from resource scarcity, increasing demand for global sustainable development. Product recycling is very important in sustainability. Product recycling is a critical link in sustainable development. By recycling and reusing waste products, we can achieve the circular utilization of resources, reduce resource consumption and waste [6], and complete the goal of sustainable development.

Product recycling is to gather, handle and remake waste articles and substances. It changes them into useful resources, thus decreasing waste of resources and environmental pollution. Disassembly, an important phase in the product recycling procedure, is to divide used articles and elements into their basic parts for reusing or remaking [7]. These parts may be composed of metal, plastic and electronic components.

As the volume of waste increases, disassembly is becoming more important, calling for more efficient and effective methods of addressing the large volume of discardable products and parts. The concept of a disassembly line arises from this problem. It contains several workstations that are responsible for performing certain tasks or processes. Mechanization and automation are used for the disassembly of scrap into parts, sorting and classification of scrap parts and the reuse of these scrap parts by recycling. But when disassembling waste products, it is important to optimize cost and benefits. That is, avoid a high construction and running cost with its own economic risk while obtaining resource utilization and environmental protection benefit. In this context, scholars have proposed DLB problems. DLB is a method of optimizing the disassembly process. It entails modifying elements, including worker locations, workflows, staffing levels, and job assignments related to disassembly. Optimizing production and financial gains while balancing the disassembly workstations' workloads is the aim [8,9]. Academics have widely explored the DLB problems, and many of them have used different approaches to tackle them.

Given the multitude of research on the DLB problems, there is an urgent need for a comprehensive review to enable researchers and scholars to better understand the latest advancements in DLB, thereby promoting further development in this field. This paper summarizes and categorizes the DLB problems to guide scholars in clarifying future research directions. We retrieved 135 articles from the Web of Science database, of which approximately 80% were published between 2020 and 2025, reflecting the rapidly increasing research interest in DLB problems in recent years. This paper offers an intuitive understanding of the methods and optimization objectives employed to solve DLB problems in recent years.

The contributions of this paper are fourfold:

- **Survey of Recent Literature:** This paper offers an in-depth study of recent literature on DLB problems. This survey equips researchers with a comprehensive and profound understanding of the current state and trends of DLB research.
- **We present a complete summary and categorization of the investigated literature in this paper.** In addition to introducing the current situation of DLB research, we also give a detailed categorization of the solving methods and optimization goals. This summary and categorization assist us in easily recognizing the strengths and weaknesses of various research strategies, and their applicability and efficiency in solving DLB problems.
- **We give an extensive description of potential future research areas for DLB problems in this study.** According to the present research situation and development tendencies, we suggest some possible research directions and explain the significance and difficulties of these directions. This analysis can help researchers to understand their research priorities, thus promoting the progress of DLB problems more efficiently.
- **We provide a framework for various DLB models for the first time.** This framework serves as a clear and organized reference for researchers' studies. It helps researchers to better understand and compare other DLB models, so they can choose the most appropriate model for their research requirements. Additionally, this framework can be used as a foundation for developing new DLB models, which will lead to new research opportunities.

The rest of this essay is structured as follows: In Section 2, the material from the literature is examined, and the study methodology is described. Section 3 introduces four common types of disassembly diagrams and discusses the concept of these diagrams. We offer a thorough explanation of the examined and categorized papers in Section 4. Within Section 5, we show several significant forms of current DLB models. Finally, Section 6 outlines future research directions and provides a summary and discussion of the study's results

## 2. Methodological Discussion

The Grounded Theory Literature Review Method from Wolfswinkel et al. [10] is cited in this section's discussion of the literature review methodology used in this work. The Grounded Theory Literature Review Method entails methodically comparing and analyzing data in the literature, in contrast to traditional techniques that only gather and summarize the material. This process extracts relevant concepts, categories, and themes, which are then combined into a verifiable and operational theoretical model. This method aids researchers in understanding problems and phenomena in a specific field and in generating new theoretical knowledge. Wolfswinkel et al. divided this method into five steps: Define, Search, Select, Analyze, and Present. Inspired by this, we have merged the last two steps into one. In the following, we will discuss in detail the four steps used in this paper according to Wolfswinkel et al. [10].

### 2.1. Define

This paper restricts the search to the past decade to conduct a systematic literature review of DLB problems. Initially, considering the quality of journals, we confined the search to journals with a specific impact factor. However, due to the limited number of articles found, we ultimately broadened the search to encompass a broader range of journals. This allowed us to conduct a more comprehensive evaluation and screening. Additionally, we identified industrial engineering as the appropriate research field.

### 2.2. Search

Literature searches start with the definition of search terms. In this study, we define search terms such as DLB and integer programming, as illustrated in Table 1. We use the Web of Science Core Collection database for the literature search. We search for the determined search terms in the title, abstract, and keyword sections of the search engine. We iteratively screen and filter search terms using 'AND' or 'OR' relationships. The search results often include duplicate literature and some seemingly relevant but irrelevant literature, which are screened and eliminated. During the search process, we found that the previously set search terms were not comprehensive enough, so we adjusted the vocabulary.

**Table 1.** Literature search keywords.

| Search Keywords                                       |        |                                       |
|-------------------------------------------------------|--------|---------------------------------------|
| Disassembly line balancing problem<br><br>Disassembly | AND/OR | Integer programming                   |
|                                                       |        | Dynamic programming                   |
|                                                       |        | Physical programming                  |
|                                                       |        | Exact cutting-plane algorithm         |
|                                                       |        | Artificial bee colony algorithm       |
|                                                       |        | Local search algorithm                |
|                                                       |        | Genetic algorithm                     |
|                                                       |        | Greedy algorithm                      |
|                                                       |        | Beam search algorithm                 |
|                                                       |        | Simulated annealing algorithm         |
|                                                       |        | Particle swarm optimization algorithm |
|                                                       |        | Gravitational search algorithm        |
|                                                       |        | Tabu search algorithm                 |
|                                                       |        | Ant colony optimization algorithm     |
|                                                       |        | Hybrid algorithm                      |
|                                                       |        | Stochastic                            |
|                                                       |        | Fuzzy                                 |

### 2.3. Select

At this stage, we performed a rigorous literature selection process through duplicate removal and multi-level screening based on titles, abstracts, and full-text content. To further enhance the literature quality, we also conducted forward and backward citation tracking.

Publications were discarded if they: (1) concentrated only on assembly line balancing without taking into consideration the disassembly problems; (2) dealt with disassembly sequence planning but neglected the line balancing; (3) did not contain clear optimization models or definite solution procedures; or (4) were conference abstracts, editorials, book chapters or repeated investigations.

All possible relevant papers were evaluated separately by the investigators during a step-by-step procedure of title selection, abstract checking and detailed full-text investigation. Finally, 135 documents published from 2003 to 2025 were chosen for this study, about 80% of which appeared between 2020 and 2025, indicating the increasing attention paid to the dynamic line balancing (DLB) issues in recent times.

#### 2.4. Analyze and Present

At this stage, we conduct a thorough analysis and organization of the selected literature, extract relevant concepts and themes, compare and synthesize the content of each document, identify commonalities and differences, and classify and summarize them. This report reviews the state of the research on DLB problems during the last several years. Therefore, we conduct a statistical analysis of the publication years of the selected literature to ensure a complete reflection of the existing situation, as shown in Figure 1. As seen in Figures 2 and 3, we also gather information on the journals and conferences of the chosen literature in order to confirm the validity and significance of the assessed literature as well as the caliber and objectivity of the research. This data can help researchers determine the leading publications in the research field, better understand the development direction and trends, and participate in related conferences to expand their research network and find potential partners.

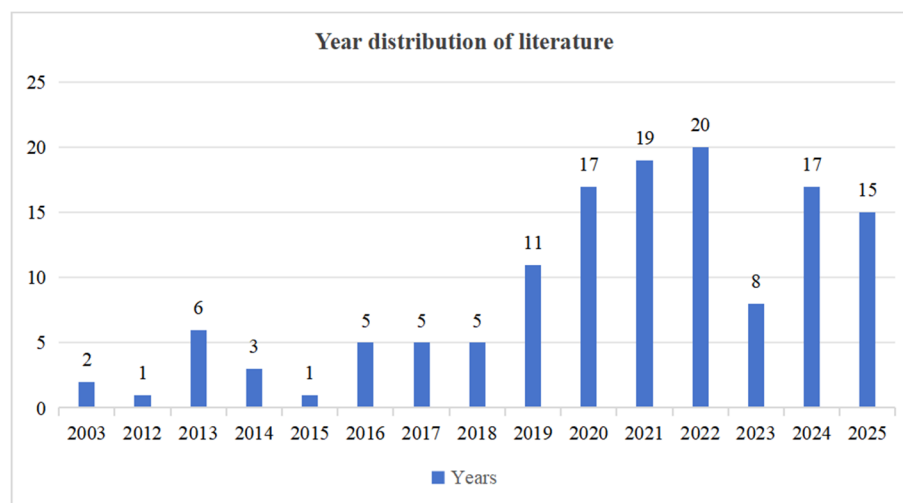


Figure 1. Number of literatures by year.

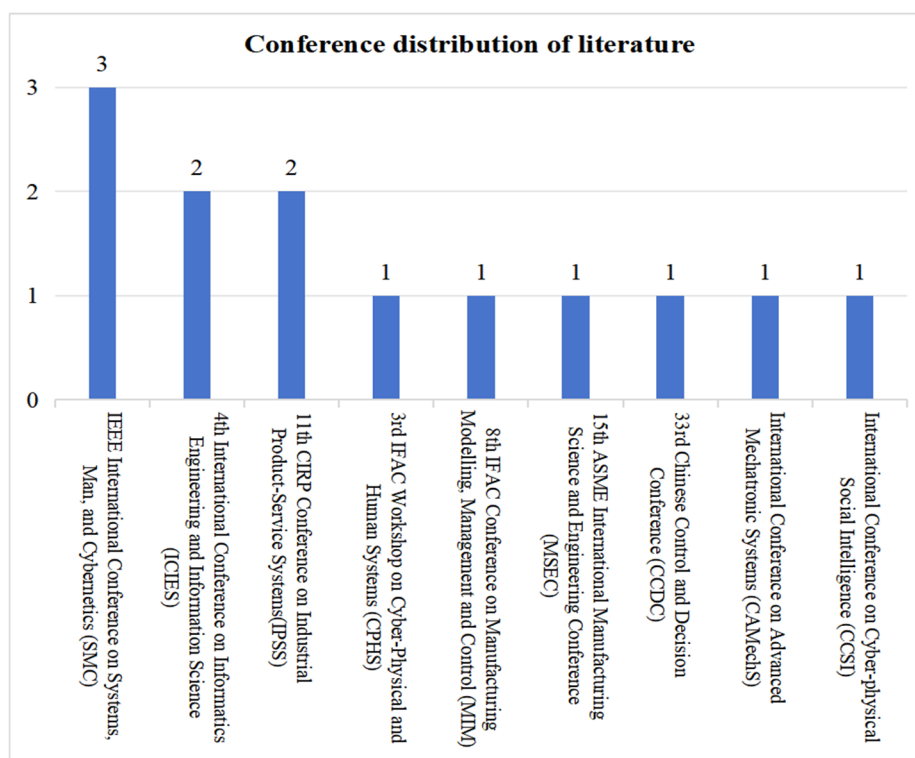
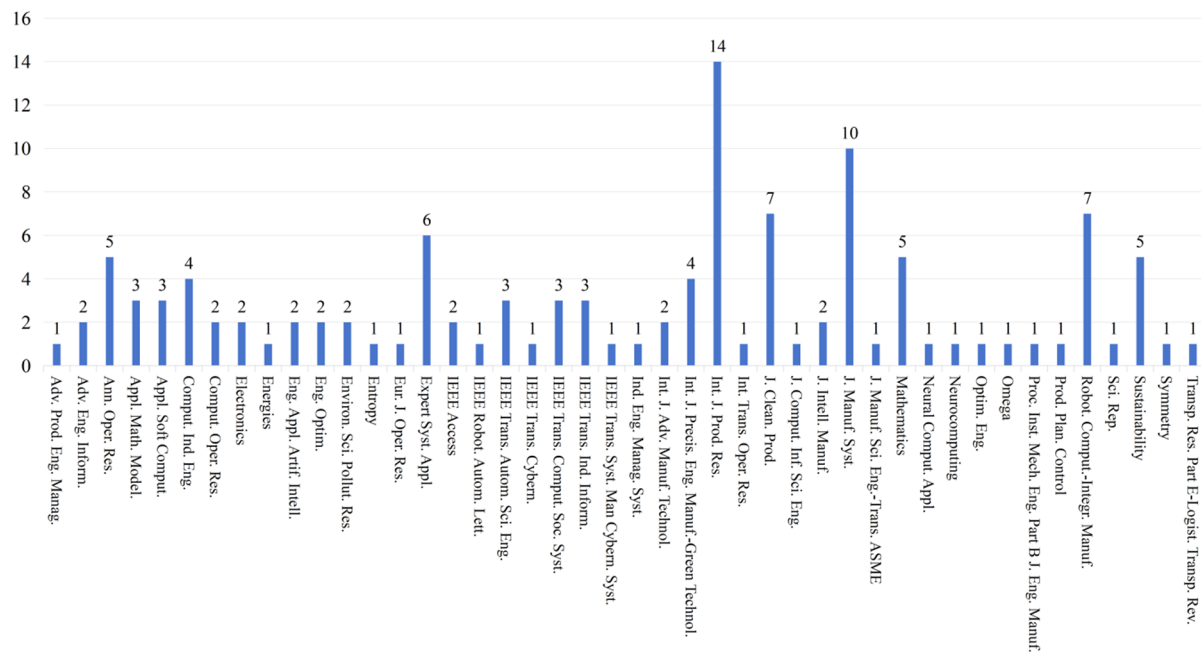


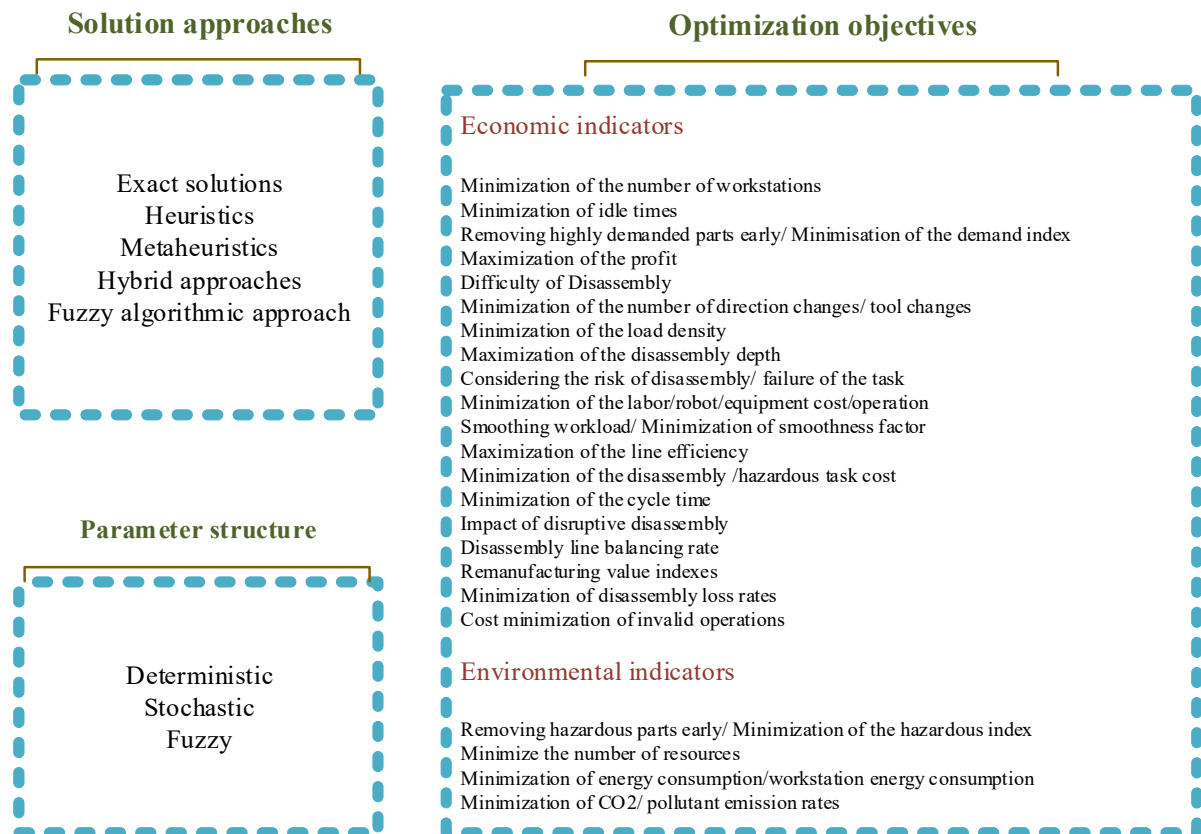
Figure 2. Distribution of the amount of literature among the proceeding.





**Figure 3.** Distribution of the number of literature in each journal.

Finally, we summarize all the optimization objectives, solution approaches, and parameter structures in DLB problems for researchers to clarify the research status, as shown in Figure 4. We separate the economic and environmental optimization objectives of DLB problems. The solution approaches refer to the mathematical models and methods designed based on the optimization objectives in DLB problems, such as exact, heuristic, and metaheuristic approaches. DLB problems usually involve multiple uncertain factors, which have stochastic and fuzziness, may be affected by unpredictable external factors, and are generally difficult to quantify accurately. Therefore, we summarize the parameter structures, such as deterministic, stochastic, and fuzzy.



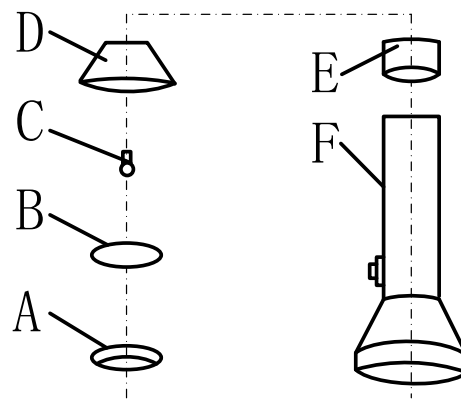
**Figure 4.** Summary and Conclusion.

### 3. Expressions of Disassembly

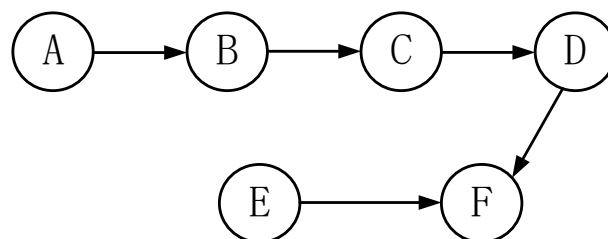
Before summarizing and analyzing the literature we collected, let's introduce the disassembly graph theory. An assembly consists of several physically connected sub-assemblies, which include components and parts [11]. Before disassembling the product, it's necessary to understand the assembly structure and familiarize oneself with the structural characteristics and constraints of the components to obtain an accurate disassembly plan. The AND/OR graph, Petri net, task priority graph, and parts priority graph are the main topics of this section.

#### 3.1. Part Priority Graph

The part priority graph is made up of nodes and directed lines. The nodes can stand for only a single part, and the required line represents the precedence constraint relationship between two parts [12]. The constraint relation between the parts clearly shows the disassembly sequence of the parts. When a node has a constraint relation with many nodes simultaneously, the node belongs to the particular constraint set, which further provides the structural connection between parts. Gungor and Gupta were the first to introduce part priority diagrams from the assembly problem into the disassembly process [13]. However, interactive and knowledge inference methods are needed to obtain the disassembly sequence information, which will cost much labor. At the same time, it is too concise to express the specific knowledge of the component. The following describes the flashlight structure as an example [14], as shown in Figure 5. Based on the priority sequence relationship when the flashlight is disassembled, its part priority diagram model can be constructed [14], as shown in Figure 6.



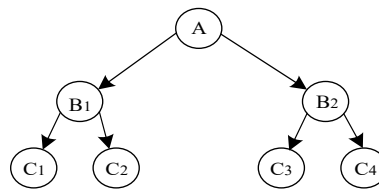
**Figure 5.** Flashlight composition schematic diagram.



**Figure 6.** Parts priority diagram of flashlight structure. A—Flashlight top cover, B—Flashlight glass piece, C—Bulb, D—Reflective Mirror, E—Flashlight rear end cap, F—Flashlight housing.

#### 3.2. Task Priority Graph

The elemental composition of the task priority graph is the same as that of the part priority graph, which also consists of nodes and directed lines. The part priority graph differs in that it represents disassembly tasks as nodes rather than parts and orders them according to the priority of the tasks. Each branch point represents a disassembled sub-component with a clear hierarchy and expression. Subtasks that are identical and inappropriate for intricate disassembly tasks may yet arise under branch points. Parts and disassembly chores have a complex relationship that is difficult to describe. Figure 7 shows the task priority graph of a product. A means the original product, B represents the subassembly, generating new subassemblies by disassembly, and C stands for the final-disassembled individual components obtained from subassemblies.

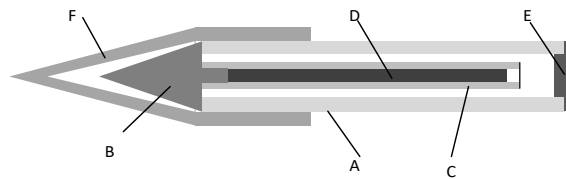


**Figure 7.** Task priority diagram for a product.

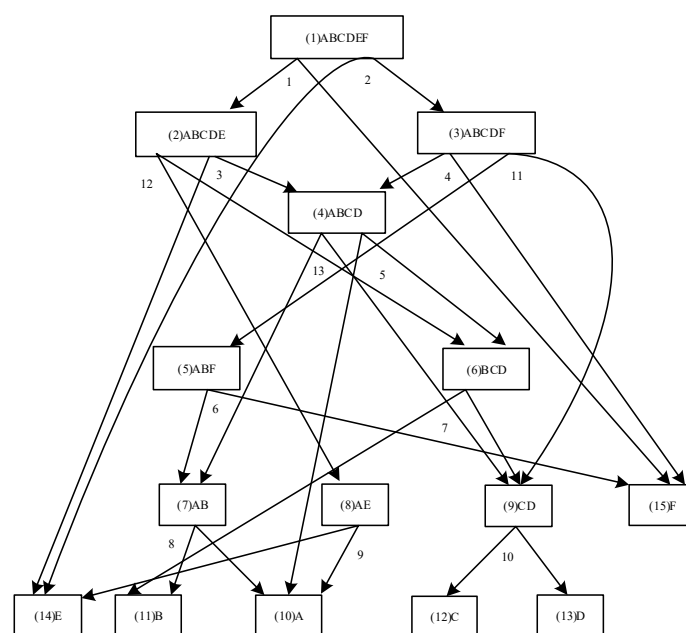
### 3.3. AND/OR Graph

This mathematical model was initially applied to the assembly problem of each part and can directly reflect the priority relationship between each sub-assembly. Nodes and directed edges are also present in today's AND/OR graph. Sub-assemblies, comprising parts and components, are represented by the AND/OR graph nodes, which are denoted by numbers in brackets. Directed edges are bi-directional arcs that can point to two nodes simultaneously, representing demolition tasks, and are characterized by numbers. Performing the disassembly task of the AND/OR graph, two sub-assemblies to which it refers can be obtained simultaneously, and logically, the two assemblies obtained are related in terms of the existence of the relationship AND. Some nodes have more than one bi-directional arc below them, indicating that multiple disassembly tasks can decompose these sub-assemblies and that multiple bi-directional arcs under the same node are in an OR relationship with each other [12]. The model can express the concurrency of all disassembly tasks and sequences, especially disassembly tasks. However, the shortcomings are apparent when the disassembly of too many parts and the structure is too complex. The resulting coexistence is also significantly increased, making it easy to produce a 'Combination explosion' problem [15].

Moreover, there is no disassembly constraint relation, so the AND/OR graph is suitable for simple disassembly tasks. Regarding disassembly, scholars such as Zussman and Min have extensively researched the AND/OR graph [16–18]. Taking the ballpoint pen in Figure 8 as an example [19], we can obtain the disassembly AND/OR graph in Figure 9.



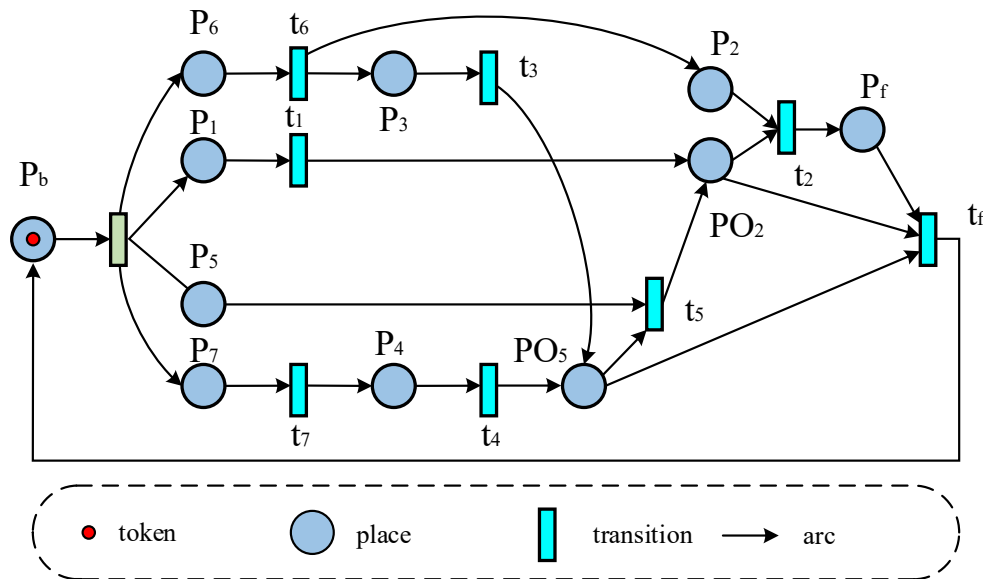
**Figure 8.** Ballpoint pen structure diagram. A—Pen-barrel, B—Pen-tip, C—Ink tube, D—Refill core, E—Rear cover, F—Pen-cone.



**Figure 9.** Ballpoint pen disassembled AND/OR graph. A—Pen barrel, B—Pen tip, C—Ink tube, D—Refill core, E—Rear cover, F—Pen cone.

### 3.4. Petri Net

Physicist Carl Adam Petri proposed the Petri net in the 1960s [20], and its first applications were in computer, automation, and control disciplines [21]. The Petri net serves as an extended version of the AND/OR graph. It comprises four parts: place, transition, connection, and token [22]. Place represents the subassembly, transition represents the disassembly task, connection represents the mutual transmission between place and transition, and token represents the state and properties of the subassembly. Based on the properties of Petri nets, scholars such as Gungor, Gupta, Zussman, and Zhou have introduced them to the disassembly problem [17,21]. The disadvantages are similar to the AND/OR graph, as the expression is more specific, and the model is more complex than the AND/OR graph. The ‘combination explosion’ problem is more likely to arise than with an AND/OR graph when there are too many components, making it challenging to represent them graphically. A product’s Petri network structure is depicted in Figure 10 [23].



**Figure 10.** A product disassembly of Petri net structure.

Lastly, Table 2 provides a summary of the advantages and disadvantages of the various disassembly graphical theories discussed earlier.

**Table 2.** Essential characteristics of the four disassembly modeling techniques.

| Model Categories    | Advantages                                                                                                                             | Disadvantages                                                                                                                |
|---------------------|----------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------|
| Part priority graph | The constraint relationships between parts and the disassembly sequence can be clearly expressed.                                      | Understanding if the modeled process is extensive or has many interdependent parts can become quite complex and challenging. |
| Task priority graph | Ability to clearly articulate the sequence of disassembly tasks                                                                        | Difficulty in modeling                                                                                                       |
| AND/OR graph        | The ability to express the disassembly sequence in an orderly manner can effectively describe the concurrency of the disassembly work. | Poor integration and prone to combinatorial explosion.                                                                       |
| Petri net           | It is easy to form comprehensive disassembly models that can express concurrent disassembly tasks.                                     | Difficult to solve nonlinearly                                                                                               |

## 4. Analysis and Discussion

We go over the optimization techniques and goals in this section, which are based on the solution approaches that are summed up as classification criteria in Section 2. This section reviews the algorithms of DLB problems in five aspects: exact algorithm, heuristic algorithm, intelligent algorithm, fuzzy algorithmic approach, and multi-attribute decision-making.

#### 4.1. Exact Algorithms

The exact algorithm is a strategy that can identify the optimal solution to DLB problems. The exact algorithm can discover the best solution in a reasonable period when the problem size in combinatorial optimization is small. However, the exact algorithm does more than only solve the issue as it grows larger; it also gives the heuristic algorithm a starting point for finding better solutions by providing a workable solution. Integer programming is the most common type of exact algorithm. A Mixed Integer Programming (MIP) model was created by Edis et al. [24] to solve direction variation, quantity demanded, part hazards, and balancing difficulties in DLB problems. This model is aimed at reducing hazards and directional changes of part disassembly, offering a more effective optimization of these problems compared to heuristic methods. A MIP model for the sequence-dependent U-shaped DLB problem was developed by Li et al. [25], and it can solve practical problems on a small scale. A MIP model was presented by Mete et al. [26] to rebalance disassembly lines in response to shifting supply and demand. In order to reduce cycle time and the total amount of workstations, Cil [27] created a MIP model. A nonlinear MIP model was employed by Ozceylan and Paksoy [28] to ascertain the best distribution of low-cost workstations and low-cost facilities. An enhanced MIP model was created by Yin et al. [29] to reduce cycle time, energy usage, and hazard index. Ozceylan et al. [30] employed a nonlinear MIP model to reduce the cost of workstations in terms of transportation, purchase, and refurbishment. In addition to integer programming, exact algorithms such as dynamic programming and physical programming are also utilized to solve DLB problems. Zhou et al. [31] adopted a multiobjective dynamic programming approach with a backward recursive algorithm to minimize workstations and operating costs. A linear physical programming-based technique for balancing mixed-model disassembly lines was presented by Ilgin et al. [32], highlighting the significance of economic disassembly processes for the profitability of product recovery.

#### 4.2. Heuristic Algorithms

The heuristic algorithm can give feasible solutions to large-scale DLB problems faster than the exact algorithm. Nevertheless, it does not necessarily mean that the result is the optimum. Usually, it is difficult to determine how near the obtained solution is to the best one. In this paper, the local search algorithms, a broad category of algorithms capable of solving iterative problems efficiently, are introduced. The fundamental principle of these algorithms is to iterate in the proximity of the solution such that the objective function is locally optimized until further optimization is not possible. For the sequence-dependent U-shaped DLB problems, Li et al. [25] suggested an iterated local search algorithm and a mixed-integer programming model. They highlighted the advantages of employing U-shaped lines rather than straight lines and demonstrated how their approach outperforms existing algorithms in terms of efficiency and search speed. McGovern et al. [33] suggested a greedy algorithm for efficiently balancing disassembly lines. Their method takes into account components that are hazardous and in high demand while attempting to reduce the number of workstations. Another greedy algorithm was created by McGovern and Gupta [34] to accomplish the goal of lowering the overall number of workstations further. This algorithm prioritizes the removal of components that are hazardous and in high demand. Mete et al. [35] suggested a beam search-based method to reduce the amount of workstations. They highlighted its competitiveness and potential for further research. This underscores the diversity and adaptability of heuristic algorithms in addressing DLB problems.

#### 4.3. Intelligent Algorithms

In intelligent algorithms, people apply methods to deal with complicated engineering issues by imitating natural phenomena based on the natural laws. Genetic algorithm (GA), artificial bee colony (ABC), ant colony optimization (ACO), particle swarm optimization (PSO), simulated annealing (SA), tabu search (TS), firefly algorithm (FA) and other kinds of intelligent algorithms have been established and improved since the beginning of the twenty-first century to solve DLB problems. In this context, we will introduce some important algorithms as well as the newest and combined ones.

##### 4.3.1. Simulated Annealing

The SA algorithm provides a superior solution compared to local search algorithms. It avoids being trapped in local minima by utilizing probabilistic bursts during the searching procedure and ultimately achieving the global optimum. Kizilay et al. [36] used a combination of mixed-integer linear programming and constraint programming models with SA meta-heuristics to efficiently dismantle products with intricate AND/OR precedence relations and dependent setting times. Their research emphasizes the significance of decreasing the number of workstations.

Wang et al. [37] designed a special SA algorithm to enhance the disassembly profit while minimizing the number of workstations and workload smoothing. In another study, Wang et al. [38] proposed a partial disassembly method based on a genetic SA algorithm and a precedence graph. This approach can reduce the energy usage, increase the profit and take into account the risks of disassembly. Subsequently, Wang et al. [39] obtained better outcomes in terms of disassembly efficiency and economic benefits by reducing the number of workstations, optimizing the workload and raising the profit through a genetic SA method and a parallel partial DLB model. Their method is more effective than the previous ones. Fang et al. [40] also established a mixed integer mathematical programming model and a SA based heuristic to optimize the dismantling process, considering the depreciation of cycle time, workstation energy consumption and overall energy consumption. Finally, Liang et al. [41] developed an improved mixed-integer programming model and a dual-individual SA algorithm for a two-sided DLB problem. Their model considers the reduction of workload smoothing and total energy consumption, demonstrating the flexibility and efficiency of SA algorithms in solving DLB problems.

#### 4.3.2. Genetic Algorithm

The GA computer model simulates the processes of biological evolution and natural selection. It's a technique for finding the best answers by imitating how things naturally evolve. Researchers frequently use GA to address DLB problems. Ren et al. [42] used a method of asynchronous parallel disassembly planning that does not require synchronization. They solved this problem using GA to define a quicker disassembly process for large products. In order to compute a mathematical model that optimizes the quantity of robots and workstations, the overall load density, the expense of hazardous jobs, and the rate of CO<sub>2</sub> emission, Liu et al. [43] presented a GA. For their DLB problem, Wang et al. [44] created a multiobjective GA with the goal of reducing the amount of stations while balancing the demand index, harmful index, idle time, and multiple direction shifts. Their approach has been verified to be effective in two case studies. A 2-sided DLB issue was described by Kucukkoc [45], who provided a potent GA technique called 2-GA to solve it quickly and effectively, producing optimal or nearly optimal solutions. For their DLB problem, Chen et al. [46] suggested a mathematical model and a three-phase heuristic adaptive GA in order to reduce the amount of laborers needed. Experimental results indicate superior performance. Jiang et al. [47] created a disassembly system that uses a multiobjective GA and a mathematical model for scheduling and resource allocation in order to minimize the predicted overall makespan and cost. In order to optimize the amount of stations, smoothing index, energy consumption, and demolition profit, Wang et al. [48] created an enhanced GA. In order to optimize disassembly lines for DLB problems with correlated jobs in electronic waste recycling by minimizing workstations and maximizing task relationships, Cheng et al. [49] developed an integer nonlinear programming model and an adaptive GA. Meng and Zhang [50] adopted and improved a multiobjective GA to calculate a disassembly model that considers the parts' failure characteristics and material hazard constraints as the optimization objectives. Dalle Mura et al. [51] developed a multiobjective formulation and a GA to optimize disassembly lines for efficiency and safety with two real-world case studies, minimizing idle time and maximizing disassembly profit while prioritizing dangerous parts removal. Finally, Yilmaz and Yazici [52] presented an algorithm based on the GA for optimizing the total cost and cycle time and balancing the efforts. This underscores the versatility and effectiveness of GA in addressing DLB problems.

#### 4.3.3. Artificial Bee Colony

One specific use of swarm intelligence is the ABC algorithm, which uses optimization to simulate bee behavior. Its primary characteristic is that it merely requires a comparison of the topics' respective strengths and weaknesses—a thorough discussion of the issues is not necessary. With a fast convergence rate, the swarm eventually produces the optimum global value through each worker bee's local optimization-seeking behavior. ABC is also widely used to address the DLB problems. A hybrid ABC approach was presented by Wang et al. [53] to solve sequence-dependent DLB problems. A multiobjective ABC method was demonstrated by Xu et al. [54] in an effort to boost profits by lowering the overall energy consumption, disassembly complexity, and workstation count. In order to solve sequence-dependent DLB problems with numerous objectives, Kalayci and Gupta [55] used the ABC method and demonstrated its superior performance over other algorithms. In order to solve restrictions and precedence among sections, Zhang et al. [56] created a 2-sided DLB problem model using a hybrid graph and a multiobjective optimal strategy based on an ABC algorithm. The goal was to decrease the amount of workstations, idle time, and smoothness index. A discrete multiobjective ABC algorithm was presented by Wang et al. [57] to calculate a DLB model in order to increase productivity and profitability while reducing workload. Through a series of comprehensive computer tests, they proved the effectiveness of the suggested model and algorithm. For their sequence-dependent DLB problem, Liu and Wang [58] introduced an improved discrete ABC algorithm that

beats nine other methods in terms of efficiency and multiobjective optimization. This is essential for the remanufacturing sector to safeguard the environment and use resources efficiently. Cao et al. [59] developed a novel multiobjective optimization method using a two-population discrete ABC algorithm for a DLB problem to comprehensively consider time, energy, and value efficiencies in remanufacturing operations. Wang et al. [60] developed a discrete ABC algorithm to minimize makespan and energy consumption. In order to decrease workstations and energy consumption, Gao et al. [61] suggested an energy-efficient optimization technique for their DLB problem. This method leverages the ABC algorithm to combine energy usage with cost and workload targets. Li et al. [62] reduced the number of stations for the DLB problem on U-shaped disassembly lines by using a mixed integer linear programming model and an enhanced ABC algorithm.

#### 4.3.4. Particle Swarm Optimization

The study of bird flock foraging behavior gave rise to the PSO algorithm, a developing computing technique. The fundamental thought is to identify the best solutions by collaborating and exchanging data between persons in a community. This algorithm has been widely adopted or improved by many researchers, both nationally and internationally, to address the DLB problems. In ecologically responsible and sustainable manufacturing, Kalayci and Gupta [63] introduced a PSO algorithm with a neighborhood-based mutation operator to address a sequence-dependent DLB problem. Their approach was compared to other methods to demonstrate its effectiveness. An entropy-based adaptive hybrid PSO technique was introduced by Xiao et al. [64] to address their DLB problem. They constructed a disassembly hierarchy information graph and improved population diversity, comparing their approach to other evolutionary algorithms. Tseng et al. [65] developed a closed-loop model for concurrently generating and evaluating disassembly sequences using a PSO method. They demonstrated its feasibility and efficiency in solving disassembly sequence planning problems through test results and an illustrated example product. A PSO-based selective disassembly planning approach with multi-criteria and adaptive decision-making models was introduced by Li et al. [66]. This technique can handle intricate restrictions and produce WEEE disassembly plans that are optimal. This demonstrates the PSO algorithm's adaptability and efficiency in solving DLB problems.

#### 4.3.5. Hybrid Algorithms

In addition to single metaheuristics, many research works have been done on hybrid algorithms which integrate several optimization approaches to solve the difficulties, uncertainties and multi-objectives in disassembly line balancing (DLB) problems.

At first, the hybrid methods mainly concentrated on enhancing the global exploration and avoiding the premature convergence. Kalayci et al. [67] used a genetic algorithm with variable neighbourhood search to enhance the recovery efficiency of components and materials during the end-of-life product disassembly. Pistolesi et al. [68] suggested a hybrid Genetic Algorithm for a multi-objective DLB problem which tries to maximise the profit and disassembly depth while minimising the number of workstations, showing better results than conventional algorithms.

Later, the hybrid systems were improved to deal with uncertainties, parallel structures and multiple objectives. Zhu et al. [69] developed a hybrid migrating birds optimisation algorithm including a simulated annealing-based reset mechanism to overcome the structural and quality uncertainty of the product, thereby avoiding local optimums. Zhu et al. [70] proposed a hybrid group neighbourhood search algorithm combined with simulated annealing-based local search to optimise partially parallel disassembly lines under four objectives, aiming to reduce waste and increase productivity. Wu et al. [71] put forward a multi-objective discrete brainstorming optimiser to decrease the energy consumption and improve the disassembly profit. Zhang et al. [72] presented a multi-objective hybrid evolutionary search method which integrates a new population update strategy with local search to reduce idle time and the number of workstations

Recently, some studies have introduced learning mechanisms and problem-specific adaptive strategies to further improve the performance of hybrid algorithms under complex precedence relationships and operational constraints. Yang et al. [73] investigated the multi-objective U-shaped disassembly line balancing problem with AND/OR precedence relations, and put forward a Q-learning based multi-objective teaching-learning-based optimisation algorithm (Q-MOTLBO) which combines five special local search operators with reinforcement learning to select efficient operators flexibly. Tests on 29 benchmark instances showed that Q-MOTLBO outperformed MOABC, MOGWO, NSGA-II, and other algorithms in both convergence (IGD) and solution diversity (HVR).

Huang et al. [74] addressed the energy-efficient human–robot collaborative U-shaped disassembly line balancing problem by incorporating a turn-on–off energy-saving strategy and carbon emission considerations.

They formulated a multi-objective uncertain model minimizing disassembly smoothness, energy consumption, cost, idle time, and carbon emissions, using normal cloud theory to characterize uncertainty. A hybrid ALNS–NSGA-II algorithm was proposed, combining adaptive large neighborhood search with NSGA-II through customized encoding/decoding, destruction–construction operators, and adaptive control rules. A recycled engine case study demonstrated that the proposed method outperformed NSGA-II, ALNS, and other traditional algorithms in terms of HV and IGD, while the turn-on–off strategy reduced energy consumption by 26% and carbon emissions by 3.1%.

Overall, hybrid algorithms have evolved from simple metaheuristic combinations into intelligent, adaptive, and learning-enhanced frameworks capable of addressing uncertainty, complex precedence relations, multi-objective trade-offs, and sustainability requirements, making them a dominant paradigm for solving advanced DLB problems.

#### 4.4. Stochastic Programming Approach

Stochastic programming is used to study DLB problems with uncertainty, i.e., when both the coefficients in the constraints and the parameters in the objective function are stochastic variables. For a stochastic DLB problem with little distributional information, Liu et al. [75] created a two-stage distributionally resilient formulation and an accurate cutting-plane algorithm to yield more dependable solutions than current approximation techniques. The authors Liu et al. [76] presented a novel formulation featuring distributionally resilient restrictions for a stochastic multi-product DLB problem involving workforce assignment. In order to maximize predicted profit-based disassembly and enhance the disassembly solution, Liu and Zhang [77] devised a partial disassembly sequence planning strategy with uncertainty. They achieved this by using a variable neighborhood search algorithm. Altekin [78] suggested a chance-constrained programming model for a stochastic DLB problem that aims to decrease the amount of stations while accounting for normally distributed stochastic task durations. In order to produce Pareto-optimal solutions, Aydemir-Karadag and Turkbey [79] introduced a novel GA for the stochastic DLB problem with site parallelism. This GA makes use of AND/OR graphs and combines repair methods and diversification strategies. Mete et al. [80] developed a GA and a constructive heuristic based on the Dijkstra algorithm to address a DLB problem with stochastic task durations. They then compared them with other cutting-edge techniques and showed that GA performs better. Xia et al. [81] presented an adaptive hybrid particle swarm GA optimizing their proposed problem in a complex and stochastic environment using adaptive genetic operators and weighted particles for enhanced global and local optimization and considering various disassembly factors such as load balancing and high-demand part priority. Huang et al. [82] developed a DLB model founded on an AND/OR graph that was optimized using a multiobjective discrete bat optimizer outfitted with an elite strategy and operators with the goal of optimizing benefits and minimizing energy expenditures. Wang et al. [83] presented a 2-sided partial DLB model that is stochastic. They simultaneously adjusted the amount of workstations, workload smoothness, energy costs, and profitability using a multiobjective discrete flower pollination algorithm. One such stochastic multiobjective DLB problem was introduced by Guo et al. [84]. They suggested using a multiobjective discrete grey wolf optimizer and an SA to save energy and carbon emissions while increasing the benefits of disassembly. A stochastic multiobjective disassembly sequencing and line balancing problem-based on an AND/OR graph was proposed by Zhang et al. [85]. They reduced carbon emissions and increased earnings by using a new multiobjective discrete grey wolf optimizer. Wang et al. [86] proposed a multiobjective cuckoo search algorithm to solve a stochastic sequence-dependent multiobjective DLB model with the objectives of reducing total energy consumption and increasing profit. Based on a disassembly AND/OR graph of EOL products, Wu et al. [87] suggested a novel optimizer that integrates stochastic simulation for viable solutions under the limitations of cycle time and disassembly precedence connections. The model assesses a number of variables and accounts for the possibility of disassembly failure. In order to balance a mixed-flow dismantling line, Xia et al. [88] created an adaptive simulated annealing genetic algorithm that took into account the stochastic influence of the amount of workstations, the load balancing index, and the cost minimization of erroneous operations. The goal of the bi-objective DLB problem with stochastic job processing times created by He et al. [89] is to lower the energy consumption and overall line configuration cost within a set budget. In order to tackle a stochastic DLB problem, He et al. [90] looked into two models: a distribution-free model and a bi-objective chance-constrained model. In order to propose a preferable solution based on decision-maker preferences for decreasing line design cost and cycle time, they employed two variations of the epsilon-constraint method in addition to a fuzzy-logic technique. In order to address the issue, Wang et al. [91] suggested a stochastic multiobjective DLB model based on an AND/OR graph. They offered a chemical reaction optimization algorithm that performs better than the current approaches in terms of maximizing profit and minimizing workstation and energy usage. A multiobjective GA and



stochastic model were created by Liang et al. [92] for disassembling high-volume EOL products. They demonstrated its practical application in disassembling multiple types of cars, considering workstation activation cost, workload smoothness, and hazard index. Wang et al. [93] developed a new multiobjective discrete flower pollination algorithm and a stochastic DLB model that assesses a number of variables in order to produce high-quality, workable solutions that take uncertainty, environmental preservation, and financial gains into account. Guo [94] tackled the risk of task failure in disassembly operations by introducing a hybrid metaheuristic strategy that integrates an ABC algorithm and a stochastic DLB model. This technique aims to maximize the projected recovery profit.

Recent studies have increasingly incorporated uncertainty and risk into disassembly line balancing (DLB) models. Tian et al. [95] first addressed stochastic operation times by proposing a multi-objective stochastic DLB model aimed at minimizing idle rate, workload smoothness, and energy consumption, which was solved using a modified northern goshawk optimization algorithm combined with stochastic simulation. Based on this uncertain view, Kalaycilar et al. [96] also took into account the effects of hazardous task failures which might lead to power outages and developed a two-stage stochastic programming model to obtain the maximum expected net revenue, with the assistance of a relaxation-based heuristic and upper-bound analysis. More recently, Zhang et al. [97] extended stochastic DLB modeling through a chance-constrained framework that explicitly controls service reliability by predefined confidence levels, while simultaneously incorporating human workload and failure risk constraints, and proposed a hybrid metaheuristic combining the water cycle algorithm and simulated annealing, which was validated on multiple real-world cases and outperformed several benchmark algorithms.

#### 4.5. Fuzzy Programming

Fuzzy programming is another method to handle objective functions that are not single and elastic conditions in DLB problems. The process of fuzzy programming involves adding an affiliation function, fuzzifying the objective function and restrictions, and creating a new linear programming issue. The optimal solution to this new problem is the fuzzy optimal solution of the original problem. Fuzzy multiobjective programming and binary fuzzy goal programming were presented by Paksoy et al. [98] as ways to balance each workstation's task while cutting down on cycle time and the amount of workstations. A Pareto-improved artificial fish swarm approach was presented by Zhang et al. [99] to address their multiobjective fuzzy DLB problem. In order to optimize a fuzzy DLB problem, Seidi and Saghari [100] proposed a GA that prioritizes the removal of high-demand and dangerous components while lowering the amount of workstations and idle time. Ming et al. [101] used task-based and subassemblies-based precedence diagrams along with stochastic, fuzzy, and interval programming techniques to propose a mathematical model for an extended disassembly line with multi-robotic workstations that takes into account multiple conflicting objectives and uncertainties in task processing times. In order to compute a fuzzy multiobjective two-sided DLB model and lower the disassembly loss rate, smoothness index, and energy consumption, Liang et al. [102] devised a multiobjective flatworm algorithm. Kalayci et al. [103] created a hybrid discrete ABC method and a fuzzy extension of a DLB problem using triangular fuzzy membership functions. The algorithm shows better performance than the previous ones and is applied to a new data set, indicating the adaptability and efficiency of these fuzzy algorithms in solving DLB problems.

#### 4.6. Advanced Intelligent Algorithms and Paradigm Evolution in Disassembly Line Balancing

##### 4.6.1. Methodological Foundations of Intelligent Disassembly Line Balancing

Initial research on advanced intelligent algorithms for disassembly line balancing (DLB) was mainly focused on altering and enhancing classical metaheuristics to handle the combinatorial complexity and sequence relationships in disassembly processes. These investigations laid the theoretical foundation for the improvement of intelligent DLB optimization.

Kalayci and Gupta [104] discussed the sequence-dependent disassembly line balancing problem by presenting a tabu search algorithm which gave priority to the elimination of dangerous and high demanded components in order to reduce idle time and the number of workstations. This research can be considered as one of the initial attempts to incorporate intelligent searching methods into the DLB model. Afterwards, Ren et al. [105] applied a gravitational search algorithm to find the optimal solution for the profit oriented partial DLB problem, clearly relating the decision of task selection to economic goals and showing the feasibility of using physical inspired optimization techniques in disassembly processes.

With the rising importance of multi-objective optimization, Zhu et al. [106] developed a Pareto-based firefly algorithm for Distributed Logistics Balancing (DLB) problems taking into account the number of workstations, hazard levels and workload smoothness. By using stochastic perturbation techniques, the proposed method could

avoid early convergence. Liu et al. [107] contributed to this area by suggesting an improved discrete bees algorithm for robotic DLB problems, resulting in a more even distribution of workload and higher solution diversity.

At the same time, hybrid exact-intelligent methods were also established. Cil et al. [108] presented an ant colony optimization integrated with mixed integer linear programming for DLB problems, where ACO was applied to produce good initial solutions for exact solvers. This concept was further developed by Cil et al. [109], who combined ACO with MILP to enhance the computational efficiency of large scale DLB cases. Liu et al. [110] enhanced their previous work by creating an efficient discrete bees algorithm for collaborative robotic disassembly sequence planning and line balancing, showing improved convergence and stability. Fang et al. [111] put forward a gamma-based evolutionary algorithm to solve interval multi-objective DLB problems, especially dealing with the uncertainties in task processing times. Wang et al. [112] incorporated destructive disassembly modes into a multi-objective DLB model and solved it by using a discrete flower pollination algorithm, indicating the economical benefits of controlled destructive strategies.

In summary, these early studies proved the practicability and effectiveness of intelligent and hybrid optimization algorithms for DLB problems, providing valuable methodological references for future research on more complicated and real-world disassembly situations.

#### 4.6.2. Algorithmic Enhancement and Multi-Objective Expansion

After the initial investigation of intelligent algorithms for DLB problems, research from 2021 to 2022 showed a rapid progress in developing structured swarm intelligence techniques and in establishing more complete multi-objective optimization systems. During this period, the studies paid more attention to the management of intricate precedence relationships, joint operations, various line arrangements and sustainable objectives.

Huang et al. [113] investigated the U-shaped disassembly line balancing problem and proposed a multi-objective discrete bat algorithm to reduce the number of workstations and balance the workload at the same time. The findings showed that the combination of an U-shaped arrangement and suitable swarm optimization methods could remarkably improve the disassembly efficiency. Fan et al. [114] extended the study on intelligent DLB to human-robot cooperative systems by developing a multi-objective shuffling frog-leaping algorithm. Their model improved both the disassembly profit and energy consumption, suggesting the potential for cooperative disassembly to enhance both economic and environmental aspects. Li and Janardhanan [62] analyzed the profit-oriented partial disassembly line balancing in U-shaped layouts and applied a discrete cuckoo search algorithm. Taking into account the selective disassembly options, their research demonstrated the advantages of integrating economic factors with layout-driven DLB optimization. Zhang et al. [115] incorporated carbon emission objectives into the DLB model and suggested a hybrid graph-based multi-objective optimization technique, which was the first to link disassembly optimization with the demands of low-carbon manufacturing.

In 2022, the focus of the research changed to the scalability and robustness of intelligent algorithms for solving large and strictly limited DLB problems. Qiu et al. [116] designed an improved NSGA-II algorithm with population restart and elite retention strategies to deal with a three-objective disassembly planning issue, which resulted in better convergence and solution diversity. Liang et al. [117] introduced a restart genetic flatworm algorithm to handle multi-objective DLB problems, showing improved global exploration ability and stability in comparison with conventional evolutionary algorithms.

Liang et al. [118] enhanced the applications of swarm intelligence by developing an improved social spider algorithm for resolving DLB problems which considered the number of workstations, workload balance, tool changes and energy consumption. Their results confirmed the effectiveness of socially motivated search strategies in handling complex multi-objective disassembly conditions. Zhang et al. [119] dealt with large scale scrap double-sided disassembly lines and proposed an improved whale optimization algorithm which significantly reduced the computation time without sacrificing the high solution quality. Yu et al. [120] solved the parallel mixed-flow remanufacturing disassembly line balancing problems using a non-dominated sorting genetic algorithm, indicating that evolutionary multi-objective optimization is appropriate for mixed-flow and parallel disassembly systems.

Generally, the studies during this period indicate an evolution from single algorithmic trials to more comprehensive algorithmic improvements and various application areas. By optimizing the encoding schemes, search processes and objective functions, these papers efficiently improve the capability of intelligent algorithms to solve real and large-scale DLB problems.

#### 4.6.3. Structural Complexity and Uncertainty-Aware Optimization

In 2023, the research on intelligent algorithms for disassembly line balancing (DLB) has been extended to more complex system arrangements, such as carbon-restricted disassembly, random working conditions, parallel

workstations and multi-product robotic systems. As compared with the previous works, the present stage has given more importance to the realism, versatility and strength in the design of disassembly system.

Cui et al. [121] studied a disassembly line balancing problem with carbon emission restrictions and suggested a discrete whale optimization algorithm to obtain the maximum disassembly profit under the condition of meeting the carbon emission limits. Their findings indicated that intelligent metaheuristics can efficiently handle the trade-off between economic and environmental objectives, especially when stringent emission restrictions are imposed.

To specifically deal with the uncertainties and failures in disassembly procedures, Xu et al. [122] investigated the stochastic multi-product robotic disassembly line balancing problem with disassembly failures. A Pareto-optimal multi-objective brainstorming optimizer was suggested and combined with stochastic simulation to reflect the probability of task execution. The research emphasized the necessity of integrating intelligent optimization with uncertainty modeling to enhance the solution's robustness.

In addition, many studies were conducted on the layout complexity and structural extensions of DLB systems. Zhang et al. [123] studied a knowledge-based flexible disassembly line for waste electric vehicle batteries, dividing the disassembly tasks hierarchically according to the domain knowledge and optimizing them by using a neuro-symbolic task and motion planning approach. This research indicated an important advance in combining knowledge representation with intelligent optimization in disassembly systems. Zhang et al. [124] also dealt with the stochastic disassembly line balancing problems oriented towards energy by treating the disassembly and standby energy consumption as interval variables, and suggested an enhanced social engineering optimization algorithm to deal with the energy uncertainty.

Liang et al. [125] studied the disassembly line balancing problem with multiple workstations and suggested an improved differential evolution algorithm for minimizing line length, workload imbalance and space occupation. Their findings indicated that the use of appropriate intelligent algorithms together with parallel workstation configuration could substantially enhance the system's flexibility and production rate.

Generally, the studies published in 2023 show an evident tendency towards intelligent DLB models which take into account environmental limitations, stochastic characteristics, structural intricacy and knowledge combination. These papers have also reduced the difference between the theoretical optimization models and the practical disassembly system needs.

#### 4.6.4. Learning-Assisted and Disturbance-Aware Optimization

With the rise of realistic demands in disassembly systems, papers issued in 2024 paid special attention to the uncertainty modeling, tool and equipment deterioration, preventive maintenance, joint work, and the incorporation of learning-based optimization techniques into DLB problems. This period signifies an important change from fixed intelligent optimization to adaptable and disturbance-conscious decision-making structures.

Qin et al. [126] studied the disassembly line balancing problem taking into account the deterioration of tools, where tool wear results in increased processing times and decreased operational efficiency. A profit-oriented mathematical model was established and a modified discrete migratory bird optimizer was proposed to simultaneously optimize the task allocation and tool usage decisions. In another related research, Qin et al. [127] also considered the tool degradation effects on the cycle time and system stability in DLB problems and suggested an improved Advantage Actor–Critic (A2C) algorithm with adaptive action space, which shows better performance than the traditional metaheuristics for large-scale cases.

To solve the problem of uncertainty and stochastic behavior in collaborative disassembly systems, Wu et al. [128] investigated the stochastic human–robot collaborative disassembly line balancing problems by describing the uncertain task times with probability distributions. A hybrid evolutionary algorithm was designed to simultaneously reduce the number of workstations, balance the workload and decrease the carbon emissions, which demonstrates good robustness under different levels of uncertainty. Guo et al. [129] also extended the research on human–robot cooperation by dealing with stochastic HRC-DLB problems involving AND/OR precedence relations, and suggested a Pareto improved shuffled frog-leaping algorithm to improve the convergence rate and the solution diversity.

Maintenance-related interruptions were considered in the intelligent DLB model presented by Guo et al. [130], who studied the partial multi-robotic disassembly line balancing problem with the inclusion of preventive maintenance. A four-objective optimization model was established and a multi-population cooperative coevolution artificial bee colony algorithm was suggested to balance the cycle time, relocation cost, energy consumption and disassembly profit. The results indicate the significance of incorporating maintenance strategies in the DLB optimization to enhance system stability.

Moreover, reinforcement learning was used to deal with the dynamic and hybrid layout disassembly systems. Wang et al. [131] investigated the dynamic equilibrium of U-shaped robotic disassembly lines and put forward a Deep Q-Network (DQN) approach to cope with real-time interruptions. The proposed technique demonstrated higher adaptability than the conventional optimization methods in both the standard examples and practical disassembly processes. Wang et al. [132] likewise considered the hybrid disassembly line balancing problem which includes linear and U-shaped layouts with several skilled workers, and developed a Soft Actor–Critic (SAC) algorithm which is capable of efficiently solving complex decision spaces and large-scale problems.

In addition to line-level optimization, the system-level integration under uncertainty was investigated by Hu et al. [133], who considered an integrated reverse supply chain design and disassembly line balancing problem. A two-stage stochastic programming model together with an improved Benders decomposition method was established to simultaneously optimize the facility location, equipment configuration, line balancing and inventory decisions, showing the importance of taking into account the upstream and downstream uncertainties in the disassembly system design. Moreover, heuristic-based neighborhood search methods were employed to deal with difficult DLB cases. Fathollahi-Fard et al. [134] constructed an adaptive large neighborhood search (ALNS) system for DLB problems, which not only enhanced the solution accuracy but also reduced the computational time under complicated constraints. Yang et al. [135] developed an improved multi-objective artificial bee colony (IMOABC) algorithm to solve the energy-saving disassembly line balancing problem, thereby enlarging the range of algorithms for intelligent DLB optimization.

Studies in 2024 show a methodological change towards uncertainty-aware, maintenance-integrated and learning-assisted DLB optimization. This change has prepared the way for more advanced learning-driven and system-level approaches which have been researched subsequently.

#### 4.6.5. System-Level and Adaptive Intelligent Optimization

In 2025, the investigation on intelligent disassembly line balancing (DLB) has advanced in dealing with more intricate system configurations, like multi-factory cooperation, complicated layouts, electric vehicle battery disassembly, dynamic rebalancing and new intelligent optimization techniques. As compared with the earlier phases, the research during this period regarded DLB problems as significant system-wide decisions rather than line-level optimization issues.

Guo et al. [136] studied the multi-factor disassembly line balancing problems taking into account the workers' posture restrictions and various line arrangements. A categorical Deep Q-Network (C51) algorithm was developed to represent the action-value function as a probability distribution, which improved the training stability and the robustness of the solutions. The results indicated that the distributional reinforcement learning can greatly outperform the traditional DQN, A2C and PPO methods in large-scale multifactory disassembly situations. Qi et al. [137] then extended the research of learning-based Dynamic Load Balancing (DLB) to heterogeneous multifactory remanufacturing systems by introducing a Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm. Their work mainly concentrated on the coordination of task assignment and resource usage among multiple factories, demonstrating that the actor-critic based reinforcement learning schemes are suitable for dealing with the continuous and high-dimensional decision spaces in complicated disassembly systems.

Besides reinforcement learning, the metaheuristic optimization methods have been improved to deal with new disassembly situations. Mao et al. [138] studied the disassembly line balancing of used electric vehicle battery packs by contrasting single-sided and symmetrical dual-sided arrangements. A multi-objective optimization model was established to assess the effect of the layout design on the throughput, work load balance and resource utilization, showing that the proper choice of layout is important for enhancing the disassembly efficiency in battery recycling systems.

Zhang et al. [139] studied a two-sided robotic disassembly line balancing problem with mobile robots, taking into account AND/OR precedence relations and cross-station mobility constraints. A hybrid optimization approach, combining constraint programming and lexicographic Pareto optimization, was proposed which produced acceptable solutions for complex two-sided and mobile-assisted disassembly systems. This research showed that hybrid exact-intelligent methods could be used to solve difficult DLB problems.

Wang et al. [140] discussed dynamic disturbances and real-time adaptation in their study on energy-saving disassembly line balancing and re-balancing problems taking into account the occurrence of task failures. A multi-objective optimization model was established to reduce the number of workstations, the imbalance of workload, the cost after failure adjustment and energy consumption. An adaptive multi-objective genetic algorithm based on Q-learning was proposed, showing good adaptability and convergence properties in dynamic failure conditions.

In addition, new swarm intelligence algorithms have enriched the methodology of intelligent DLB optimization. Niu et al. [141] put forward a zebra optimization algorithm to deal with complicated disassembly line balancing issues, which demonstrates good performance in aspects of convergence rate and solution accuracy in comparison with the traditional swarm intelligence methods. Zeng et al. [142] considered the robotic disassembly line balancing problems which include preventive maintenance and ordinary disassembly conditions, and suggested a multi-objective improved genetic simulated annealing algorithm to reduce the cycle time while preventing task rearrangement during the maintenance changes.

Based on these advances, Zhang et al. [143] extended the research of intelligent disassembly line balancing to a broader and more forward-looking viewpoint. Their investigation dealt with complicated disassembly situations in which the traditional static optimization is not sufficient, and stressed the combination of the new intelligent decision strategies with the disassembly process model to enhance adaptability and flexibility under changing and uncertain conditions. In contrast to the previous studies which mainly concentrated on the improvement of algorithms in fixed structures, this research emphasized the cooperation among the system framework, decision rules and total performance, showing a transition from the optimization at line level to a more comprehensive and adaptable design of disassembly systems.

Studies published in 2025 show a significant change in DLB optimization towards a system-level, adaptive and intelligence-based method. The works combine the coordination of multiple factors, the advanced arrangement design, reinforcement learning, hybrid optimization systems and maintenance-related modeling, which indicate the current advanced level of intelligent disassembly line balancing research.

Finally, as indicated in Tables 3 and 4, we provided a detailed summary of the optimization approaches and goals discussed in the literature in tables.

**Table 3.** Optimization objectives and their typical application scenarios.

| Category            | Issue                                                                     | Typical Application Scenarios                                              | References                                                                                                                          |
|---------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Economic indicators | Minimization of the number of workstations                                | High-throughput disassembly systems for large-scale WEEE recycling         | [28,29,31,33,35,37,39,43,44,46,54,56,61,62,68–70,72,73,78,80,83,88,91,93,97,98,100,104,106,108,112,118–120,125,128,129,136–140,144] |
|                     | Minimization of idle times                                                | Mixed-product disassembly lines requiring balanced workloads               | [4,29,44,52,56,69,70,72,74,87,95,97,100,104,119,134,136,138]                                                                        |
|                     | Removing highly demanded parts early/<br>Minimization of the demand index | Remanufacturing-oriented recovery systems prioritizing valuable components | [33,34,44,73,81,88,100,104,119]                                                                                                     |
|                     | Maximization of the profit                                                | Commercial remanufacturing enterprises seeking economic benefits           | [37–39,48,51,54,57,68,71,82–87,91,94,96,105,112–114,121–123,126,129,130,132,133,135,136,139,141,143]                                |
|                     | Minimization of the total disassembly time                                | Time-sensitive disassembly operations in industrial recycling plants       | [29]                                                                                                                                |
|                     | Difficulty of Disassembly                                                 | Complex products with multiple fastening and joining methods               | [54]                                                                                                                                |
|                     | Minimization of the number of direction changes/ tool changes             | Robotic or automated disassembly cells                                     | [44,115,116,118]                                                                                                                    |
|                     | Minimization of the load density                                          | Human–robot collaborative disassembly environments                         | [43,88]                                                                                                                             |
|                     | Maximization of the disassembly depth                                     | End-of-life products requiring maximum component recovery                  | [68]                                                                                                                                |
|                     | Considering the risk of disassembly/ failure of the task                  | Uncertain disassembly environments with stochastic failures                | [38,87,94]                                                                                                                          |
|                     | Minimization of the labour/robot/equipment cost/operation                 | Labor-intensive or automated recycling facilities                          | [27,30,31,43,46,47,52,70,75,76,89,90,92,97,117,129,134]                                                                             |

Table 3. Cont.

| Category                 | Issue                                                             | Typical Application Scenarios                                        | References                                                                                       |
|--------------------------|-------------------------------------------------------------------|----------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|
| Economic indicators      | Smoothing workload/<br>Minimization of smoothness factor          | Multi-station disassembly lines with workload balancing requirements | [37,39,41,48,52,56,57,61,73,81,83,92,93,95,98,102,106,112,117,118,128,134,140]                   |
|                          | Maximization of the line efficiency                               | High-productivity disassembly systems                                | [38,57,123,124]                                                                                  |
|                          | Minimization of the total cost                                    | Cost-sensitive industrial recycling operations                       | [74,137,138]                                                                                     |
|                          | Minimization of the disassembly /hazardous task cost              | Hazardous WEEE treatment plants                                      | [43,123,124,138,139]                                                                             |
|                          | Minimization of the cycle time                                    | Mass-processing disassembly systems                                  | [4,27–29,40,47,52,70,90,98,109,111,125,126,129,132,139,142,143]                                  |
|                          | Impact of disruptive disassembly                                  | Dynamic disassembly environments subject to disturbances             | [117]                                                                                            |
|                          | Disassembly Line Balancing rate                                   | Flexible mixed-model disassembly lines                               | [120,122,125,135]                                                                                |
|                          | Remanufacturing value indexes                                     | Value-oriented remanufacturing decision-making                       | [120]                                                                                            |
|                          | Minimization of disassembly loss rates                            | High-value component recovery system                                 | [102]                                                                                            |
|                          | Cost minimization of invalid operations                           | Intelligent disassembly planning under uncertainty                   | [88]                                                                                             |
| Environmental indicators | Removing hazardous parts early/minimizing the hazardous index     | WEEE treatment facilities handling toxic components                  | [29,33,34,44,51,73,87,92,100,104,106,128]                                                        |
|                          | Minimize the number of resources                                  | Sustainable and resource-efficient disassembly systems               | [69]                                                                                             |
|                          | Minimization of energy consumption/workstation energy consumption | Low-carbon manufacturing and green remanufacturing                   | [29,37,38,40,41,48,60,61,71,74,82,84–87,91,93,95,97,102,111–114,118,122,125,129,130,139,140,143] |
|                          | Minimization of CO <sub>2</sub> /pollutant emission rates         | Carbon-neutral disassembly and circular economy systems              | [43,74,84,85,90,115,121,128,133,135]                                                             |

Table 4. Solution approaches.

| Category               | Approaches                                               | References                              |
|------------------------|----------------------------------------------------------|-----------------------------------------|
| Exact algorithms       | Integer programming                                      | [24–30,40,41,46,51,62,78,92,98,108,119] |
|                        | Dynamic programming                                      | [31]                                    |
|                        | Physical programming                                     | [32]                                    |
|                        | Exact cutting-plane algorithm                            | [75]                                    |
| Heuristic algorithms   | Local search algorithm                                   | [25]                                    |
|                        | Greedy algorithm                                         | [33]                                    |
|                        | Beam search algorithm                                    | [35]                                    |
| Intelligent algorithms | Simulated annealing algorithm                            | [36,38,40,41,83]                        |
|                        | Genetic algorithm                                        | [42–52,79,80,92,100]                    |
|                        | Artificial bee colony algorithm                          | [53,54,56–63,108]                       |
|                        | Particle swarm optimization algorithm                    | [55,64–66]                              |
|                        | Ant colony optimization algorithm                        | [109]                                   |
|                        | Discrete zebra optimization algorithm                    | [121,141]                               |
|                        | Improved multi-objective artificial bee colony algorithm | [135]                                   |

Table 4. Cont.

| Category               | Approaches                                                                              | References  |
|------------------------|-----------------------------------------------------------------------------------------|-------------|
| Intelligent algorithms | Multi-objective improved genetic simulated annealing algorithm                          | [142]       |
|                        | Adaptive multi-objective genetic algorithm based on Q-learning                          | [140]       |
|                        | Improved water cycle algorithm                                                          | [136]       |
|                        | Multiobjective enhanced differential evolution algorithm                                | [125]       |
|                        | NeuroSymbolic task and motion planning                                                  | [123]       |
|                        | Multi-objective shuffled frog leaping algorithm                                         | [129]       |
|                        | Constraint programming-based lexicographic-Pareto approach                              | [139]       |
|                        | Categorical DQN                                                                         | [136]       |
|                        | Multi-population cooperative coevolution artificial bee colony algorithm                | [130]       |
|                        | Constraint programming models                                                           | [124]       |
|                        | Multi-objective immune genetic algorithm                                                | [128]       |
|                        | Improved Benders decomposition approach                                                 | [133]       |
|                        | Non-dominated Sorting Genetic Algorithm and Non-dominated Sorting Genetic Algorithm     | [138]       |
|                        | Hybrid evolutionary algorithm                                                           | [128]       |
|                        | Improved multi-objective water cycle algorithm                                          | [139]       |
|                        | Improved multi-objective genetic algorithm based on Q-learning                          | [143]       |
|                        | Adaptive large neighborhood search algorithm                                            | [134]       |
|                        | Multi-objective enhanced differential evolution algorithm                               | [97]        |
|                        | Improved grey wolf optimization algorithm                                               | [130]       |
|                        | Modified discrete migratory bird optimizer                                              | [126]       |
|                        | Gravitational search algorithm                                                          | [105]       |
|                        | Tabu search algorithm                                                                   | [104]       |
|                        | Discrete bees algorithm                                                                 | [107,110]   |
|                        | Gamma based-NSGA-II                                                                     | [111]       |
|                        | Genetic flatworm algorithm                                                              | [117]       |
|                        | Shuffled frog leading algorithm                                                         | [114]       |
|                        | Flower pollination algorithm                                                            | [37,93,112] |
|                        | Pareto firefly algorithm                                                                | [106]       |
|                        | A discrete cuckoo search algorithm                                                      | [62]        |
|                        | Discrete brainstorming optimizer                                                        | [71]        |
|                        | Discrete NSGA-II algorithm                                                              | [116]       |
|                        | Whale optimization algorithm                                                            | [4,119];    |
|                        | Northern goshawk optimization algorithm                                                 | [95]        |
|                        | Discrete bat algorithm                                                                  | [113]       |
|                        | Multiobjective non-dominated genetic optimization method                                | [120]       |
|                        | Deep Q-Network                                                                          | [132]       |
|                        | LLM-assisted Dueling Deep Q-Network                                                     | [136]       |
|                        | Pareto-improved multi-objective brainstorming optimizer                                 | [122]       |
|                        | Optimized Advantage Actor-Critic algorithm                                              | [126]       |
|                        | A variable neighborhood search algorithm                                                | [77]        |
|                        | Discrete bat optimizer                                                                  | [82]        |
|                        | Discrete grey wolf optimizer                                                            | [85]        |
|                        | Cuckoo search algorithm                                                                 | [86]        |
|                        | Discrete brainstorming optimizer                                                        | [87]        |
|                        | Soft Actor-Critic algorithm,                                                            | [132]       |
|                        | Discrete chemical reaction optimization algorithm                                       | [91]        |
|                        | Artificial fish swarm algorithm                                                         | [99]        |
|                        | Twin Delayed Deep Deterministic Policy Gradient algorithm                               | [137]       |
|                        | Pareto-improved multi-objective brainstorming optimizer                                 | [122]       |
|                        | Flatworm algorithm                                                                      | [102]       |
| Hybrid algorithms      | Hybrid group neighborhood search algorithm                                              | [70]        |
|                        | Hybrid genetic algorithm                                                                | [68]        |
|                        | Hybrid migration bird optimization algorithm                                            | [69]        |
|                        | A hybrid algorithm combining genetic algorithm and variable neighborhood search methods | [67]        |
|                        | Hybrid particle swarm genetic algorithm                                                 | [81]        |
|                        | Adaptive simulated annealing genetic algorithm                                          | [88]        |

Table 4. Cont.

| Category                     | Approaches                                                                                               | References                                                    |
|------------------------------|----------------------------------------------------------------------------------------------------------|---------------------------------------------------------------|
| Hybrid algorithms            | Hybrid algorithm combined with variable neighbourhood descent method and artificial bee colony algorithm | [94]                                                          |
|                              | Q-learning-oriented multi-objective teaching-learning-based optimization algorithm                       | [73]                                                          |
|                              | Adaptive Large Neighborhood Search-NSGA II, ALNS-NSGA II                                                 | [74]                                                          |
|                              | Hybrid discrete artificial bee colony algorithm                                                          | [103]                                                         |
| Fuzzy algorithmic approaches | Stochastic                                                                                               | [37,69,75,76,77,78,79,80,81,82,84,85,86,87,88,89,90,91,93,94] |
|                              | Fuzzy                                                                                                    | [98–103]                                                      |
| Stochastic programming       | Two-stage stochastic programming + LP relaxation-based heuristic + Valid cuts-based upper bounds         | [96]                                                          |
|                              | Chance-constraint programming + Hybrid metaheuristic algorithm                                           | [97]                                                          |

## 5. Mathematical Modeling of DLB Problems

Here, we present models for classic DLB problems (Section 5.1) and stochastic DLB problems (Section 5.2). Among the stochastic DLB problems, there are two main categories: Expected Constraint Planning and Chance Constraint Planning [90]. It is significant to remember that the fuzzy DLB model is an additional model that exists in an uncertain environment. The fuzzy DLB model is composed similarly to the standard DLB model; the only distinction is that fuzzy numbers are used to represent different uncertain variables [98]. Therefore, we do not demonstrate the fuzzy DLB model. These various DLB problem models provide different methods to deal with the uncertainty and complexity in the environment. According to the particular problem situation and objectives, researchers select the suitable model to improve the product disassembly and recycling procedure, finally obtaining greater sustainable resource use and environmental advantages.

### 5.1. Classic DLB Problems

The classic DLB problems are deterministic, with disassembly-related factors being well-defined [144]. Then is the mathematical model description of the traditional DLB problems; the notations are summarized as follows:

Indices:

$m$ : Index of disassembly task number,  $m = 1, 2, \dots, M$

$n$ : Workstation number,  $n = 1, 2, \dots, N$

Parameters:

$M$ : Total number of disassembly tasks

$N$ : Maximum number of workstations

$C_t$ : Cycle time of the disassembly line

$t_m$ : Disassembly time for task  $m$

Decision variables:

$x_{mn}$ : 1, If task  $m$  is selected to be disassembled in workstation  $n$ ; otherwise, 0

$u_n$ : 1, If workstation  $n$  is opened; otherwise, 0

$$\min F = (f_1, f_2, f_3, \dots, f_z) \quad (1)$$

s.t.

$$\left\lceil \frac{\sum_{n=1}^N \sum_{m=1}^M t_m x_{mn}}{C_t} \right\rceil \leq \sum_{n=1}^N u_n \leq M \quad (2)$$

$$\sum_{m=1}^M t_m x_{mn} \leq C_t, \quad \forall n \in \{1, 2, \dots, N\} \quad (3)$$



$$\sum_{n=1}^N x_{mn} = 1, \quad \forall m \in \{1, 2, \dots, M\} \quad (4)$$

$$x_{mn}, u_n \in \{0, 1\} \quad (5)$$

Equation (1) represents the objectives that the decision-maker wants to minimize, such as time, cost, energy consumption, etc. Moving on to the constraints, Equation (2) limits the number of workstations that can be turned on, where  $\lceil \cdot \rceil$  denotes upward rounding. Equation (3) guarantees that the number of disassembly jobs per workstation does not go beyond the work beat after the number of workstations has been established. To maintain the uniqueness of each assignment, a single job can only be allocated to one workstation, according to Equation (4). Finally, Equation (5) is the binary variable in the model.

## 5.2. Stochastic DLB problems

### 5.2.1. Expectation Constrained Programming

In stochastic DLB problems with expectation-constrained planning, the uncertain variables in the disassembly process are usually represented by normal or uniform distributions. These problems are typically solved using Monte Carlo simulations combined with metaheuristic algorithms [145]. We present the primary form of the stochastic disassembly time as an example; the notations are summarized as follows:

Indices:

$m$ : Index of disassembly task number,  $m = 1, 2, \dots, M$

$n$ : Workstation number,  $n = 1, 2, \dots, N$

Parameters:

$M$ : Total number of disassembly tasks

$N$ : Maximum number of workstations

$C_t$ : Cycle time of the disassembly line

$t_m$ : Stochastic disassembly time for task  $m$

Decision variables:

$x_{mn}$ : 1, If task  $m$  is selected to be disassembled in workstation  $n$ ; otherwise, 0

$u_n$ : 1, If workstation  $n$  is opened; otherwise, 0

$$\min F = (E(f_1), E(f_2), E(f_3), \dots, E(f_z)) \quad (6)$$

s.t.

$$E\left(\left\lceil \frac{\sum_{n=1}^N \sum_{m=1}^M t_m x_{mn}}{C_t} \right\rceil\right) \leq \sum_{n=1}^N u_n \leq M \quad (7)$$

$$E\left(\sum_{m=1}^M t_m x_{mn}\right) \leq C_t, \quad \forall n \in \{1, 2, \dots, N\} \quad (8)$$

$$\sum_{n=1}^N x_{mn} = 1, \quad \forall m \in \{1, 2, \dots, M\} \quad (9)$$

$$x_{mn}, u_n \in \{0, 1\} \quad (10)$$

Equation (6) expresses the expected value of specific factors that the decision-maker wants to minimize, such as cost, time, energy consumption, etc., denoted by  $E(\cdot)$ . This expected value is the average value obtained from several random simulations. Let's move on to the constraints: A maximum of workstations that are switched on throughout the planned operating period of the disassembly task is established by Equation (7). Equation (8) ensures that the total amount of time that each workstation may be operational does not exceed the designated operating time for the disassembly procedure after the amount of workstations is determined. To maintain the uniqueness of each task, Equation (9) shows that every task can be allocated to only a single workstation. Lastly, Equation (10) defines a binary variable in the model.

### 5.2.2. Chance Constraint Planning

Under chance-constrained planning, the random variables in the model are represented by the same standard or uniform distribution as in expectation-constrained planning. However, the goal of chance-constrained planning is different. Its goal is to reduce the objective function's value to a certain degree of confidence. Additionally, it allows for the constraints to be satisfied in a probabilistic manner, providing the decision maker with the flexibility to adjust the confidence value according to their risk appetite. Just like expectation-constrained planning, the most commonly used method for solving chance-constrained planning problems involves the use of meta-heuristic algorithms combined with Monte Carlo simulations [145].

Indices:

$m$ : Index of disassembly task number,  $m = 1, 2, \dots, M$

$n$ : Workstation number,  $n = 1, 2, \dots, N$

Parameters:

$M$ : Total number of disassembly tasks

$N$ : Maximum number of workstations

$C_t$ : Cycle time of the disassembly line

$t_m$ : Stochastic disassembly time for task  $m$

Decision variables:

$x_{mn}$ : 1, If task  $m$  is selected to be disassembled in workstation  $n$ ; otherwise, 0

$u_n$ : 1, If workstation  $n$  is opened; otherwise, 0

$$\min F = (\bar{f}_1, \bar{f}_2, \bar{f}_3, \dots, \bar{f}_z) \quad (11)$$

s.t.

$$Pr(f_1) \geq a_1 \quad (12)$$

$$Pr(f_2) \geq a_2 \quad (13)$$

$$Pr(f_3) \geq a_3 \quad (14)$$

$$Pr(f_z) \geq a_z \quad (15)$$

$$Pr\left(\frac{\sum_{n=1}^N \sum_{m=1}^M t_m x_{mn}}{C_t} \leq \sum_{n=1}^N u_n \leq M\right) \geq a_{z+1} \quad (16)$$

$$Pr\left(\sum_{m=1}^M t_m x_{mn} \leq C_t\right) \geq a_{z+2}, \quad \forall n \in \{1, 2, \dots, N\} \quad (17)$$

$$\sum_{n=1}^N x_{mn} = 1, \quad \forall m \in \{1, 2, \dots, M\} \quad (18)$$

$$x_{mn} \in \{0, 1\} \quad (19)$$

The goal function's value, which is minimized at a given confidence level, is represented by Equation (11). The values of each goal function are more significant than or equal to a specified confidence level, according to Equation (12) through (15). Additionally, according to Equation (16), there is a probability that the number of workstations that must be turned on in order to meet the restrictions is more significant than or equal to a particular confidence level. Equation (17) guarantees that the likelihood of each workstation's work time staying inside the cycle time is greater than or equal to a specified degree of confidence. Equation (18) ensures that only one operation can be taken at one workstation. Equation (19) defines a binary variable in the model.

## 6. Future Research Directions and Conclusions

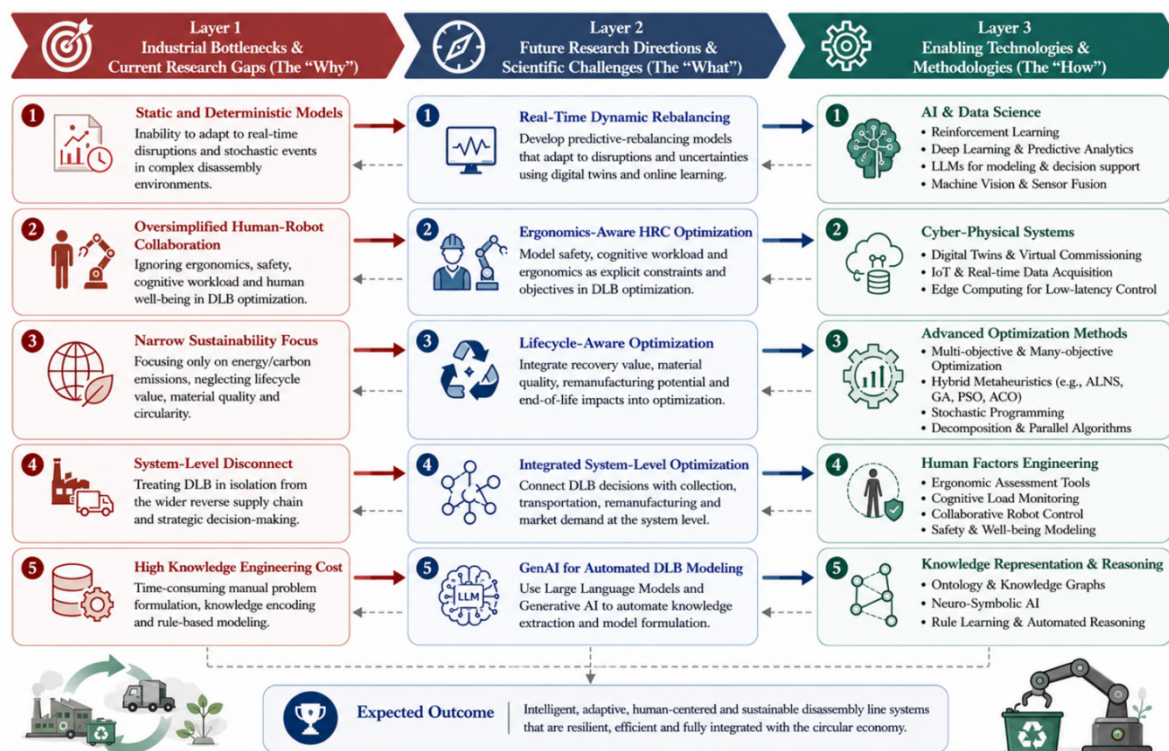
### 6.1. Future Research Directions

Despite significant progress, several critical gaps between academic DLB models and industrial practice remain [146]. To address these challenges and foster real-world deployment, future research should pivot from static, isolated, and narrowly focused paradigms toward dynamic, human-centric, and system-level frameworks [147]. Key future directions include: (1) Real-time dynamic rebalancing—integrating Digital Twins and reinforcement

learning for predictive adaptation to disruptions; (2) Ergonomics-aware human-robot collaboration (HRC)—explicitly modeling safety, cognitive workload, and physical ergonomics as optimization constraints; (3) Lifecycle-oriented sustainability—expanding objectives to include material recovery quality and circularity potential; (4) System-level integration—linking DLB decisions with upstream collection and downstream remanufacturing within the broader reverse supply chain; and (5) Generative AI for automated modeling—leveraging Large Language Models (LLMs) to automate precedence extraction and problem formulation, thereby reducing industrial deployment barriers.

To present a clear ‘problem-solution-direction’ roadmap, Figure 11 shows a future intelligent framework for DLB divided into three related layers.

As shown in Figure 11, the framework associates real industrial situations with scientific activities: Layer 1 detects the present systemic obstacles (such as model rigidity and HRC oversimplification), Layer 2 converts these into specific research problems, and Layer 3 links them to the promoting technologies like advanced AI (RL, LLMs), Cyber-Physical systems (Digital Twins, IoT) and hybrid optimization. This three-layered structure provides a comprehensive guide for guiding the DLB research towards intelligent, adaptive and sustainable disassembling systems.



**Figure 11.** A future intelligent framework for DLB: bridging research gaps and industrial bottlenecks.

## 6.2. Conclusions

Disassembly Line Balancing has changed from a conventional combinatorial optimization problem to a multi-discipline research area which combines sustainable manufacturing, intelligent optimization, uncertainty modeling and principles of circular economy. A thorough review of 135 significant papers published from 2003 to 2025 has been carried out to gain an overall knowledge of the theoretical basis, modelling methods, optimization goals and algorithm advancements in the field of DLB.

The review indicates certain advances. First, the objectives for improvement have been modified from the conventional economic indicators such as decreasing the number of workstations and balancing the workload to multi-objective considerations including energy consumption, emission of carbon dioxide, removal of hazardous materials and recovery of resources. Secondly, the solution methods have developed from exact mathematical programming and classic heuristic algorithms to a combination of metaheuristics, optimization under uncertainty and intelligent decision-making through reinforcement learning. Furthermore, the uses of Disassembly Line Balancing (DLB) have expanded from fixed systems handling single product disassembles to more realistic cases involving variable task times, interaction between humans and robots, various products, dynamic disturbances, waste batteries and intelligent remanufacturing systems.

Although there have been considerable progress, some important problems are still not solved. Presently, most investigations depend on the assumption of simple product information, operational uncertainty and unchanged production conditions, which restricts their use in actual industrial situations. Furthermore, the current optimization systems usually consider perception, planning, scheduling and execution as separate steps, thereby reducing their ability to deal with changing manufacturing environments. The combination of multi-source industrial data, real-time monitoring devices and intelligent decision-making strategies is still in its preliminary stage.

According to these observations, this review suggests six possible research topics for the future, such as adaptive optimization using digital twins, intelligent decision-making assisted by large language models, collaborative optimization by multi-agent systems, human–robot cooperation in disassembly, carbon-conscious circular manufacturing and autonomous data-driven disassembly systems. These topics show the integration of artificial intelligence, cyber-physical systems and sustainable manufacturing, offering a guideline for the next stage of DLB research.

This review not only integrates the present knowledge but also develops a systematic research scheme which connects the optimization goals, modelling techniques, supporting technologies and the forthcoming industrial needs. It is anticipated to be a useful guide for researchers and practitioners who are constructing intelligent, robust and environmentally friendly disassembly systems in the Industry 5.0 period.

### Author Contributions

J.P.: conceptualization, methodology, investigation, data curation, visualization, writing—original draft preparation, writing—review and editing; G.T.: supervision, project administration, funding acquisition, writing—review and editing; D.T.P.: validation, formal analysis, resources, writing—review and editing; H.H.: software, validation, investigation; H.C.: investigation, data curation, visualization; S.Z.: software, investigation, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

### Conflicts of Interest

Given the role as Editor-in-Chief of the journal, Guangdong Tian had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal.

### Use of AI and AI-Assisted Technologies

The authors employed ChatGPT (OpenAI) during the preparation of this paper solely for the purpose of language modification and text polishing to enhance the readability and grammatical correctness. No artificial intelligence tools were utilized to develop scientific hypotheses, screen the literature, analyze data, interpret the results or state the scientific conclusions in our work. The authors have thoroughly checked and modified all the outputs assisted by AI and take full responsibility for the originality, accuracy and reliability of the paper.

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