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Review

Artificial Intelligence in Electric Vehicle Battery Disassembly: A Systematic Review

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Abstract: The rapidly increasing adoption of electric vehicles (EVs) globally underscores the urgent need for effective management strategies for end-of-life (EOL) EV batteries. Efficient EOL management is crucial in reducing the ecological footprint of EVs and promoting a circular economy where battery materials are sustainably reused, thereby extending the life cycle of the resources and enhancing overall environmental sustainability. In response to this pressing issue, this review presents a comprehensive analysis of the role of artificial intelligence (AI) in improving the disassembly processes for EV batteries, which is integral to the practical echelon utilization and recycling process. This paper reviews the application of AI techniques in various stages of retired battery disassembly. A significant focus is placed on estimating batteries' state of health (SOH), which is crucial for determining the availability of retired EV batteries. AI-driven methods for planning battery disassembly sequences are examined, revealing potential efficiency gains and cost reductions. AI-driven disassembly operations are discussed, highlighting how AI can streamline processes, improve safety, and reduce environmental hazards. The review concludes with insights into the future integration of electric vehicle battery (EVB) recycling and disassembly, emphasizing the possibility of battery swapping, design for disassembly, and the optimization of charging to prolong battery life and enhance recycling efficiency. This comprehensive analysis underscores the transformative potential of AI in revolutionizing the management of retired EVBs.

Keywords: artificial intelligence; electric vehicle battery disassembly; state-of-health estimation; disassembly sequence planning; disassembly operation

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1. Introduction

In recent years, the greenhouse effect has become increasingly severe, and the issue of carbon emissions has become the focus of many countries and individuals. With the popularity of low-carbon and environmental protection initiatives, electric vehicles (EVs) have progressively become a trend to replace fuel vehicles due to their advantages of lower energy consumption when driving the same mileage. According to IEA Global EV Outlook [1], as shown in Figure 1, electric car sales have continued to rise over these years in most parts of the world. However, this also brings new challenges, including recycling lithium batteries. In the production process of EVs, the manufacturing consumption of lithium batteries is enormous. If retired electric vehicle batteries (EVBs) are not recycled, they will cause severe environmental pollution and even risk of fires and explosions. Therefore, the safe and sustainable treatment of retired EVBs is urgent. Currently, the disassembly of lithium batteries in the industry is often destructive and direct, as shown in Figure 2a [2–4]. The main recycling methods are pyrometallurgical recycling [5] and hydrometallurgical recycling [6]. Both recycling methods require a battery to be broken down and sorted first, removing the casing and other non-metallic materials. These two recycling methods can only recover part of the raw materials, and the recycling efficiency is relatively low. Retired EVBs typically retain 80% of their original capacity.

Scrapping and directly recycling these retired EVBs would result in a significant waste of resources. Dismantling retired EVBs and then recycling the disassembled parts separately can significantly improve recycling efficiency.

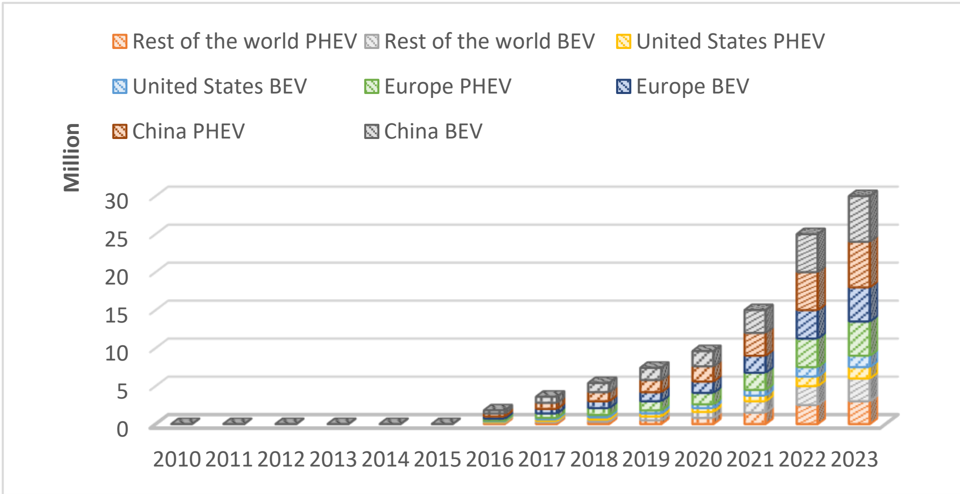

Figure 1. Global electric car stock trends, 2010–2023 (adapted from [1]). Notes: BEV = battery electric vehicle; PHEV = plug-in hybrid vehicle.

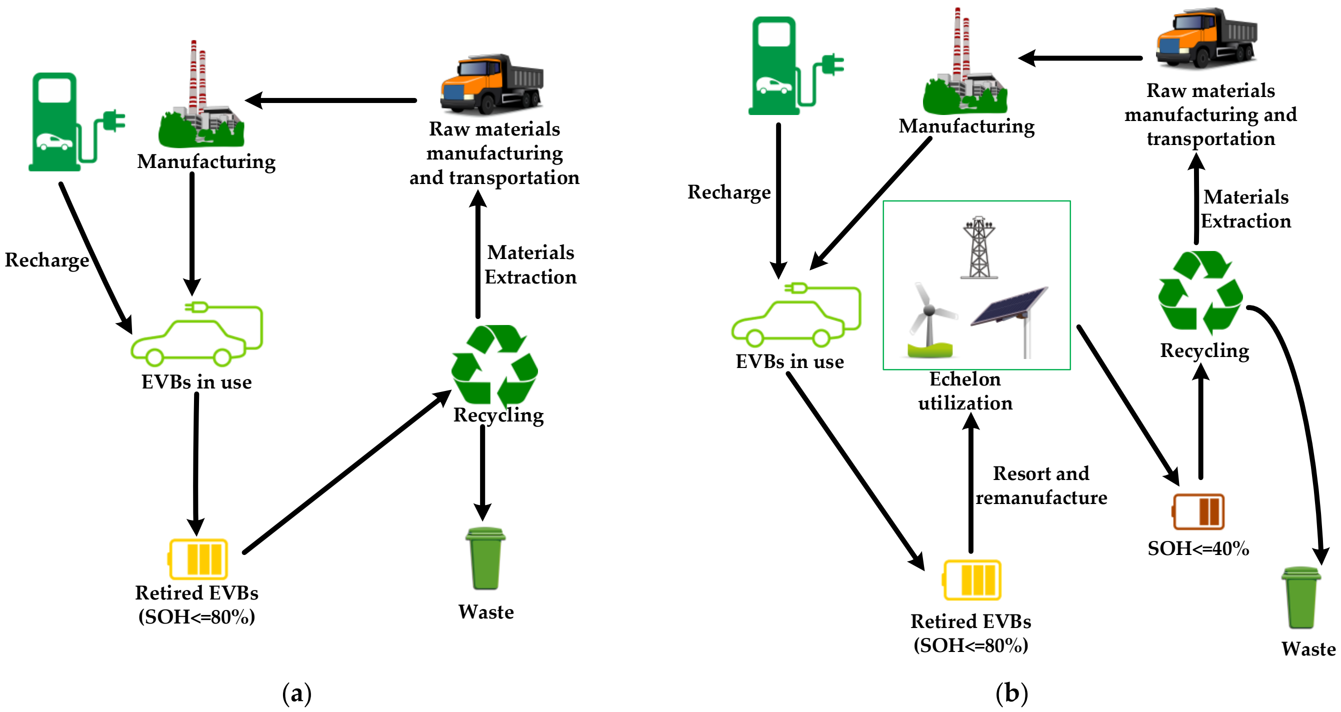

Figure 2. Life cycle of retired EVBs (adapted from [7]). (**a**) Direct recycling; (**b**) echelon utilization.

When an electric vehicle battery's state of health (SOH) is lower than 80%, it must be forcibly retired from EVs. However, such batteries still have specific use values. Currently, there is an optimization solution, namely echelon utilization [8], as shown in Figure 2b. This approach uses a battery's remaining life before it is scrapped, and it can be used in other areas, such as wind farms. Since wind energy has the characteristics of uncertainty in power generation time and power, using these scrapped batteries in wind farms can temporarily save electrical energy. When the health status of these batteries drops to about

50%, it becomes necessary for them to be scrapped [7]. This review will introduce the application of AI to the electric vehicle battery disassembly process.

The current recycling method mainly extracts raw materials, but this method has low returns. In addition, the battery must be shredded first, both in pyrometallurgical recycling and hydrometallurgical recycling. The improper handling of EV batteries may cause a fire and a risk of explosion [9]. In contrast, an efficient method is to disassemble the battery and then recycle it completely. According to the degree of automation, the battery disassembly process can be divided into several categories, namely manual disassembly, semi-automatic disassembly, and fully automated disassembly. Automated disassembly has gradually become a significant trend since there are certain safety risks in the disassembly process. However, the disassembly process is not necessarily the reverse process of the assembly process. Given the different usage situations of EV batteries and different structures from various brands, there may be significant differences between disassembly planning and actual operations, so full automation still needs to be explored in the EV battery disassembly field.

Artificial intelligence (AI) synthesizes computer science, logic, and many other disciplines. AI algorithms simulate human intelligence behaviors to perform tasks, such as decision-making and learning [10,11]. AI has achieved remarkable results in applications, such as image recognition, natural language processing, intelligent robots, etc. Given that AI can help improve the accuracy of detection and automation of disassembly, it is widely used in the disassembly process, such as EVB state-of-health (SOH) estimation and disassembly operations.

Given the significance of retired EVB disassembly and AI potential in this field, summarizing the latest technical advances is highly valuable. This review focuses on the application of AI in the EVB disassembly process, including SOH estimation, disassembly sequence planning, and disassembly operations. To improve the comprehensiveness of this review, the use of AI in other product disassembly processes is also examined, as well as the potential application opportunities of those techniques to EVB disassembly. This survey examines recent research papers on topics related to artificial intelligence, end-of-life EV batteries, state-of-health estimation, disassembly sequence planning, and disassembly operations. Many reviews on similar topics were found during the search, as shown in Table 1. Still, they focused more on the chemical recycling process of lithium batteries or just part processes in battery disassembly. This survey aims to provide a more comprehensive summary of AI applications in the EVB disassembly process. The contributions of this paper are as follows:

1. This paper summarizes the current status of electric vehicle batteries' recycling and current issues in the recycling process.
2. The applications of AI in the recycling of retired electric vehicle batteries, including SOH estimation, disassembly sequence planning, and disassembly operations, are reviewed.
3. Possible future development directions for EVB recycling are discussed.

This article introduces the application of AI to EVB disassembly and the challenges that exist in the EVB disassembly sequence and its steps. The structure of the paper is as follows: Section 2 presents an overview of EVB disassembly problems, including EVB structures and the challenges faced. Section 3 summarizes the AI-based SOH estimation models to assess the remaining useful life of the battery so as to determine whether the battery needs to be fully disassembled. Section 4 discusses disassembly sequence planning to establish the order of the disassembly operations. Section 5 presents AI-driven disassembly operations for EV batteries. Section 6 presents discussions and prospects for EVB disassembly. Section 7 summarizes the key conclusions. A list of abbreviations precedes the references section.

Table 1. Related reviews about EV battery disassembly and recycling processes.

Year	Research focus	Authors
2019	Lithium-ion battery recycling, including pyrometallurgical recovery, physical materials' separation, hydrometallurgical metals' reclamation, direct recycling, and biological metals' reclamation.	Harper et al. [12]
2022	Regulations and new battery directive demand, including current material collection, sorting, transportation, handling, and recycling practices.	Neumann et al. [13]
2022	Artificial intelligence and machine learning applications in EV battery disassembly, including preprocessing, disassembly planning and operation, intelligent interaction and collaboration, and smart design for disassembly.	Meng et al. [14]
2023	LIB recycling methods, including pretreatment, pyrometallurgical recycling, hydrometallurgical recycling, the direct recycling of spent cathode materials, the direct recycling of graphite anode materials, and advanced in situ characterization methods.	Ji et al. [15]
2023	The comprehensive recycling of lithium-ion batteries, including pretreatment, deactivation, dismantling, crushing, and the separation and treatment of electrolytes and solid components.	Yu et al. [16]
2024	Challenges and opportunities for second-life batteries, including battery degradation models, technical assessment procedures, and economic assessment.	Gu et al. [17]
2024	Human–robot collaboration-based EV battery disassembly, including product modeling, disassembly planning, and disassembly operations.	Li et al. [18]
2024	Interpretation from different directions about electric vehicle battery systems' disassembly, including process steps, the level of automation, the use of digital technologies, the level of implementation, and efficiency consideration.	Hertel et al. [19]
2024	A more systematic summary of artificial intelligence applications in electric vehicle battery disassembly, including battery state-of-health detection, disassembly sequence planning, and disassembly operation.	This review

2. Overview of Electric Vehicle Battery Disassembly Problems and Methodology

2.1. Electric Vehicle Battery Structures

Depending on the dielectric materials used, batteries can be classified into lead-acid, nickel-based, sodium-based, and lithium-based batteries. Lead-acid batteries have stable voltage and a low price but low energy density [20]. They are widely used in uninterruptible power supply systems and backup power supplies. Nickel-based batteries include nickel-cadmium batteries and nickel–metal hydride batteries [21]. Nickel–cadmium batteries are commonly used in power tools, such as drills and saws, because of their high discharge rate and long service life. Nickel–metal hydride batteries are also used in some power tools, especially those with high environmental protection requirements. Sodium-ion batteries generally have better thermal stability and safety, reducing the risk of overheating and thermal runaway, but compared to lithium-ion batteries, sodium-ion batteries have a slightly lower energy density [22]. Lithium-ion batteries (LIBs) have the advantages of a high energy density, a high power density, a long life, and no memory effect, so they are widely used in electric vehicles [23]. LIBs are typically formed by an anode, a cathode, an electrolyte, and a separator. The anode and cathode are made of lithium-metal oxide and graphite. LIB packs usually contain a battery module and a battery management system (BMS) [24].

In addition, each module contains multiple tightly packed battery cells to increase energy density and efficiency. Numerous battery modules form a battery pack, which is installed in the chassis of an electric vehicle and used to power a car [25]. The large number of batteries further increases the difficulty of disassembly.

The multiplicity of car manufacturers results in a wide variety of batteries. For example, Tesla has adopted cylindrical-type batteries [26], while Volkswagen uses prismatic battery solutions [27]. Traditional EVBs can be divided into cylindrical, prismatic, and pouch solutions according to the cell's shape [12]. Some new battery structures have emerged in recent years. BYD introduces a new type of blade battery [28]. The diversity of battery structures poses significant challenges to automated disassembly.

2.2. Challenges in the EVB Disassembly Process

During the EV battery recycling process, the following problems are encountered:

1. Low recycling efficiency: In industry, dismantling EVBs is mainly based on destructive dismantling. This method breaks the battery down into smaller parts for further processing through mechanical damage or other means. While this method allows for the rapid separation of battery components, it often damages many valuable components within the battery such that these components cannot be recycled.
2. Various types and structures: Different manufacturers use different types of batteries. For example, Tesla uses cylindrical batteries [16], while BYD uses blade batteries [29]. Battery capacity and appearance vary somewhat, even between models from the same vendor. Such a large variety of types and configurations makes automated disassembly difficult.
3. Safety risks: End-of-life car batteries contain heavy metals and toxic and hazardous organics, which may release harmful gases during treatment, posing a safety risk to operators.
4. High disassembly complexity: The disassembly process has much higher complexity than the assembly process. Many retired EV batteries have rusted screws or even deformed battery structures within them, requiring recognition algorithms to verify the situations; thus, they cannot be disassembled using just the reverse process of the EVB assembly process. Sometimes, the disassembly space is restricted, making it inconvenient for the human and/or robot arm to operate.
5. Unpublished data: Most manufacturers do not disclose their vehicles' operating data, which can result in, for example, too little training data for the state-of-health estimation process.

2.3. Methodology

This review adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [30]. The databases used were Scopus, Web of Science, and Google Scholar. Table 2 shows the keywords used in the search process. As shown in Figure 3, after duplicate papers in different databases were deleted, papers that could not be downloaded or were not relevant to the research topic were excluded. Only papers related to AI applications in EV battery disassembly were retained. These papers mainly include papers on AI in EV battery state-of-health estimation, disassembly sequence planning, and disassembly operations.

Table 2. Search databases and keywords.

Database	Keywords
Scopus	TITLE-ABS-KEY (electric AND vehicle* OR ev*) AND ALL (batter*) AND ALL (disassembl* OR dismant*) AND ALL (artificial AND intelligence OR ai)
Web of Science	(((AB=(electric vehicle* or ev)) AND AB=(batter*)) AND AB=(artificial intelligence or ai))
Google Scholar	"electric vehicle* OR EV*" AND "batter*" AND "disassembly OR dismantle*" AND "artificial intelligence OR AI"

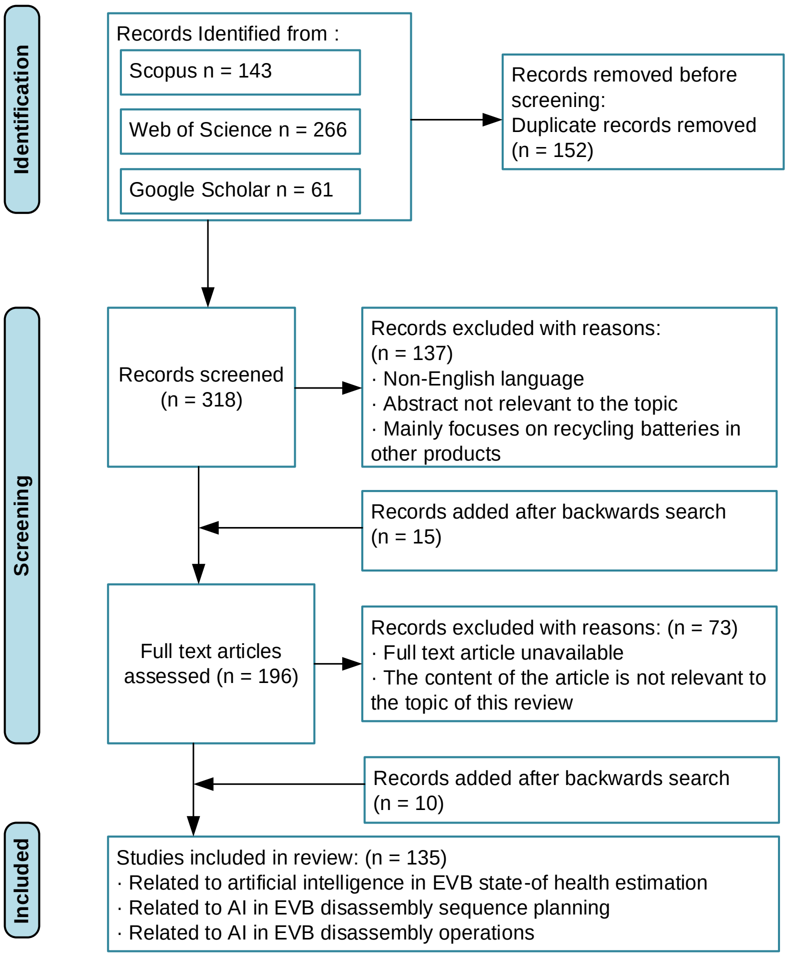

Figure 3. Systematic review results shown in the PRISMA flow diagram.

3. AI-Based Electric Vehicle Battery State-of-Health Estimation

The state of health (SOH) is a crucial indicator of the health of lithium-ion batteries. It reflects the performance and longevity of the battery during its service life, as well as the relative health of the current state compared to the battery's initial state. SOH is usually expressed as a percentage; 100% means the battery is in optimal condition, and 0% means the battery has failed or is close to failure. The direct calculation method of SOH is as shown in Equation (1) [31], where Q_{max}/mAh = the maximum charge available of the battery, and C_r = the rated capacity.

$$\text{SOH}/\% = 100\frac{Q_{max}}{C_r} \tag{1}$$

EVB SOH evaluates its present performance compared with the fresh state. When the SOH value is lower than 80%, it is regarded as being at its end of life (EOL) and must be obligatorily retired from the electric vehicle. It can be disassembled to the cell level, and then each cell is tested for SOH; cells with similar usage conditions are reassembled into batteries for echelon utilization or other small electric motorcycles; if the SOH value is lower than 50%, they need to be disassembled entirely [16]. Unfortunately, the SOH value of the battery on an electric vehicle cannot be measured directly. SOH estimation is closely related to the battery usage history. Standard prediction methods are based on capacity, resistance, voltage, current, and temperature [32]. The traditional measurement method removes the battery and measures the internal resistance. Although some non-destructive testing methods have been proposed, such as ultrasonic testing and X-ray scanning, the accuracy of these methods is generally low [33]. Since AI has advantages in data processing, it is widely used in battery SOH estimation. In recent years, there have been some reviews on EVB SOH estimation, but they have focused more on the underlying estimation methods and algorithms. Yang et al. [34] discussed various SOH estimation methods based on capacity, impedance, and aging mechanism parameters, analyzed current SOH diagnosis and prediction challenges, and discussed future development trends. Manoharan et al. [35] reviewed the application of artificial neural networks, gradient boosting, and support vector machines for electric vehicle battery state of charge (SOC) and SOH estimation. Li et al. [36] reviewed the development of a remaining service life (RUL) prediction for lithium-ion batteries based on machine learning. They discussed the application of different algorithms, including recurrent neural networks (RNNs) and support vector machines (SVMs). This section compares characterization parameters and algorithms in SOH estimation, analyzing their characteristics, advantages, and disadvantages.

3.1. AI Methods in SOH Estimation

AI-based methods, such as transfer learning, reinforcement learning, neural networks, etc., are widely used in EVB SOH estimation. AI-based battery SOH estimation usually involves offline training and online estimation. During training, informative health indicators are extracted from aging data. The AI-based model then learns and updates its weights and biases to fit this training data. After the model is well trained, it is applied to the battery management system (BMS) to estimate the real SOH based on raw data [37]. Ruan et al. [38] proposed a lithium-ion battery health-state estimation method based on a convolutional neural network and transfer learning, using data from the constant-current and constant-voltage charging conversion stage to achieve high-precision and robust SOH prediction. Li et al. [39] proposed a health-conscious battery state estimation method based on deep transfer learning, which collects and processes battery operating data through a cloud platform, significantly improving the accuracy and stability of different electric vehicle battery models. Li et al. [40] proposed an end-to-end framework based on a hybrid neural network and Bayesian optimization for SOH estimation and the RUL prediction of lithium-ion batteries for electric vehicles, verifying its high accuracy and robustness. Couture et al. [32] proposed a transfer learning hybrid model that combines images and health indicators, experimentally verified its efficiency and accuracy in battery SOH estimation and RUL prediction, and demonstrated the potential of image data in regression tasks. AI-based methods used in the SOH process include random forest (RF), long short-term memory (LSTM), transfer learning (TL), support vector machine (SVM), and convolutional neural networks (CNNs). Table 3 describes the methods and their advantages and disadvantages.

Table 3. Summary of AI-driven methods for EVB SOH.

AI Method	Description	Advantages	Disadvantages	Ref.
RF	A powerful and flexible ensemble learning method that improves model accuracy and robustness by combining multiple decision trees.	• High prediction accuracy and generalization ability. • Reducing the risk of model overfitting. • Can evaluate the importance of individual features. • High robustness.	• High computational complexity. • Poor model interpretability. • Not suitable for real-time predictions.	[41–44]
LSTM	A recurrent neural network capable of learning and remembering long-term dependencies; often used to process sequence data such as time series analysis and natural language processing.	• Suitable for processing time series data. • Solving the vanishing gradient problem	• Long training time. • Requires many data. • High complexity.	[45–49]

Table 3. *Cont.*

AI Method	Description	Advantages	Disadvantages	Ref.
TL	Using knowledge learned from one task (the source task) to aid the learning process in another related but different task (the target task).	• Low data requirements. • Speeding up the training process.	• Requires dependencies between source and target tasks. • Hard to turn pre-trained models.	[39,50–57]
SVM	A powerful and flexible supervised learning algorithm that handles linear and nonlinear classification tasks by maximizing inter-class margins and using kernel functions.	• Suitable for data with higher dimensions. • Strong robustness. • Able to handle non-linear classification problems	• High computational complexity. • Sensitive to parameter selection. • Sensitive to missing data.	[58–61]
CNN	A powerful deep learning model that automatically extracts features through convolutional and pooling layers and that is widely used in tasks such as image classification, target detection, and image segmentation.	• Can automatically extract features. • Parameters can be shared. • Preserving the spatial relationship of local features.	• High computing resource requirements. • Requiring many data. • Sensitive to input size.	[62–67]

3.2. Characterization Parameters in SOH Estimation

In EVB SOH estimation, commonly selected characteristic parameters include capacity, temperature, impedance, etc. Battery capacity is a crucial parameter describing the battery's SOH. In a laboratory, capacity loss can be measured directly by charging or discharging a battery at a nominal current until the cut-off voltage is reached. However, performing this process in practice is challenging due to device and battery operating range limitations. He et al. [68] proposed a revised Lorentzian function-based voltage–capacity (RL-VC) model. New features of interest (FOIs) are extracted from constant-current charging data by fitting the RL-VC model. They determined that the FOI highly correlated with battery capacity through correlation analysis and calibrated the linear model for SOH estimation. Galeotti et al. [69] discussed lithium polymer batteries' performance and SOH estimation through electrochemical impedance spectroscopy (EIS) techniques. Experimental results show that the ohmic resistance of the battery increases with aging, and SOH can be evaluated through the relationship between ohmic resistance and available capacity. When a lithium-ion battery operates, it generates or absorbs heat, leading to fluctuations in temperature. Chen et al. [70] proposed a SOH estimation method based on temperature prediction and a gated recurrent unit (GRU) neural network. They extracted multi-dimensional health features from differential temperature profiles to reflect multiple aspects of battery degradation. Table 4 shows the advantages and disadvantages of these characteristics. These AI-based estimation methods can achieve high accuracy. However, it should be noted that these prediction methods can sometimes only serve as auxiliary decision-making and cannot replace the actual detection process. When there are many battery cells, and the usage of different battery cells is different, heterogeneity is likely to occur. In this case, AI-based detection methods may not be effective.

Table 4. Summary of characteristic parameters for SOH estimation.

Parameter	Description	Advantages	Disadvantages	Ref.
Capacity	• The amount of electricity a battery can store when fully charged. • Usually expressed in ampere-hours (Ah).	• Directly reflects battery SOH. • The estimation is the most accurate.	• Requires a complete charge-discharge cycle, time-consuming, not suitable for real-time monitoring	[68,71–79]
Impedance	• The battery's resistance to alternating current, including ohmic resistance, polarization resistance, etc.	• Highly sensitive to changes in the internal state of the battery. • Can detect minor aging characteristics.	• Complex measurement and data processing. • Requires specialized equipment and extensive electrochemical knowledge.	[69,80–87]
Temperature	• Temperature changes caused by thermal effects during battery charging and discharging	• Can be monitored in real-time.	• Highly influenced by environmental factors. • Indirectly reflect the SOH of the battery.	[70,88,89]

4. Disassembly Sequence Planning (DSP) for EV Batteries

Disassembly process modeling and AI algorithms are two primary considerations in AI-driven disassembly sequence planning (DSP). The traditional approach involves disassembly engineers manually formulating a disassembly sequence based on years of experience and technical manuals. This method relies on personal experience and is relatively flexible, but it is prone to subjective bias, and it is less efficient when faced with complex disassembly tasks.

4.1. Disassembly Process Modeling

Disassembly representation and modeling are critical for efficient disassembly sequences and operations. Several factors influence the feasibility of a disassembly sequence, including the relationship between components, the constraints involved in disassembling the components, the geometry of the product, hazardous characteristics of disassembly, the tools required for the operation, and the components needed to disassemble the target component. The feasibility of the disassembly sequence depends mainly on the product's structure. How the product structure is represented directly affects the efficiency of the disassembly sequence search [90]. The main modeling methods are AND/OR graph modeling, Petri Net (PNt) modeling, and matrix-based modeling [18].

4.2. AI Algorithms in DSP

AI methods are widely studied in DSP. Xiao et al. [91] proposed a human–machine collaborative disassembly optimization method based on multi-agent reinforcement learning, which improved disassembly efficiency and safety by optimizing the disassembly sequence and task allocation. Hartono et al. [92] proposed a method to optimize robot disassembly plans using a bee algorithm to maximize profits, save energy, reduce the environmental impact, and achieve the automation and efficiency of the disassembly sequence in the remanufacturing process. Gao et al. [93] proposed a multi-agent strategy optimization method based on partially observable deep reinforcement learning to improve the efficiency and safety of human–machine collaboration in order to dismantle scrapped electric vehicle batteries. Allagui et al. [94] proposed a reinforcement learning-based disassembly sequence planning optimization method to improve disassembly efficiency and reduce costs by reducing tool and direction changes. Chu et al. [95] proposed a human–machine collaborative disassembly optimization method based on hybrid particle swarm optimization and Q-learning algorithms to improve the efficiency and safety of EOL EVB disassembly. The authors also developed some algorithms for disassembly planning on other products. These algorithms can also be considered for battery disassembly. A summary of these methods is given in Table 5.

Table 5. Summary of EVB disassembly sequence planning models.

Methods		Description	Applications	Ref.
Machine learning	Dynamic Bayesian network	• Calculate and compare different numbers of observation sequences through reasoning and observation sequences to verify the possibility of finding the optimal disassembly sequence.	EV battery	Xiao et al. [96]
	Q-network	• Learn optimal decisions by interacting with the environment to maximize cumulative rewards.	No mention	Allagui et al. [94]
	Q-learning	• Learn optimal policies by updating state–action value functions. • The reward function is based on the disassembly time and target component status.	Smartphone	Chen et al. [97]
	Multi-agent reinforcement learning	• Improve disassembly efficiency and safety by dynamically adjusting disassembly task assignments and paths. • Multiple agents can work together in a shared environment.	EV battery	Xiao et al. [91]
Metaheuristics optimization algorithm	Bees algorithm	• A swarm intelligence optimization algorithm based on bees' foraging behavior.	Gear pump	Hartono et al. [92]
	Artificial Bee Colony Algorithm	• A mathematical model of the random disassembly line balancing problem based on expected returns is proposed.	Cell phone	Guo et al. [98]
	Genetic algorithm	• The optimal solution to the problem is found by simulating the genetic and selection mechanisms in biological evolution.	CRT TV	Wang et al. [99]
	Particle swarm optimization	• Combining the particle swarm optimization algorithm enhances global search and local search capabilities.	EV battery	Chu et al. [95]

Compared with traditional electric vehicle battery disassembly sequence planning, AI-based methods can learn and continuously optimize the strategy and improve the efficiency and accuracy of subsequent disassembly tasks. Traditional methods often rely on manual experience, while AI-based systems can automatically generate optimal disassembly strategies through large amounts of data and learning algorithms, reducing the dependence on expert knowledge. However, the performance of AI-based systems relies on large amounts of high-quality data. If the data are insufficient or noisy, the accuracy of the model may be affected, leading to unsatisfactory disassembly results. In an actual production environment, obtaining enough relevant data can be challenging, especially when dealing with new or rapidly changing battery designs. Complex AI models, especially deep learning models, usually require high-performance computing resources to train and run, which may lead to high implementation costs and time overhead.

5. AI-Driven Disassembly Operation for EV Batteries

This section discusses some AI-driven disassembly operations for electric vehicle battery disassembly.

5.1. Object and Defect Identification

The disassembly process is more complex than the assembly process, and it requires the real-time judgment of the status of the disassembly process and the product being disassembled. Target recognition plays a vital role in the disassembly process. Zhang et al. [100] used the YOLOv4 algorithm to detect screws during the disassembly process. YOLOv4 is an efficient single-stage target detection algorithm that combines advanced network architecture and data enhancement technology to achieve high-precision target detection while maintaining real-time detection speed [101]. Foo et al. [102] proposed a practical learning framework and showed how the system can learn relevant disassembly information for LCDs. After training, the system's success rate in identifying LCD parts increased significantly from 11% to 87%. Zheng et al. [103] used PointNet DNN to identify 12 parts of car engine turbochargers. This method generates point cloud data from a CAD model and simulates sensor data with different accuracy levels through a depth camera simulator for training. Foo et al. [104] proposed a method that combines image preprocessing, deep learning models, and ontological reasoning to improve the accuracy and efficiency of screw detection in automated e-waste disassembly. Li et al. [105] proposed an accurate screw detection method based on Faster R-CNN and an innovative rotating edge similarity (RES) algorithm, aiming to automatically disassemble screws in electronic scrap, especially screws on mobile phone motherboards.

AI can also be used to identify defects in components. The traditional defect recognition method is for operators to identify product defects through visual inspection. This method relies on the experience and skills of personnel. Although it is highly flexible, it is easily affected by subjective factors, such as fatigue, resulting in false detection or missed detection. AI, especially deep learning models, can automatically extract complex features from large amounts of images or data and identify subtle and complex defects. Compared with traditional methods that rely on manually set rules and features, AI can capture the details of defects more accurately. Deep learning models outperform traditional computer vision algorithms in terms of accuracy and processing time, which has led to their widespread use in defect detection [106]. Tabernik et al. [107] proposed a two-stage deep learning architecture, including a segmentation network and a decision network. This design allows the model to be trained using fewer training samples, which is suitable for situations where defect samples are limited in practical applications. Medak et al. [108] solved the defect detection problem in ultrasound images by introducing the EfficientDet deep learning architecture, demonstrating its great potential and superiority in practical applications. Zhang et al. [109] proposed a semi-supervised learning method based on generative adversarial networks (GANs), which effectively improves the performance of automatically detecting and segmenting image surface defects while reducing the reliance on large amounts of annotated data.

However, AI models, especially deep learning models, require many annotated data for training. For defect recognition, this means collecting and annotating many images or data sets containing different types of defects. This data acquisition and annotation process is time-consuming and expensive, especially when defect samples are scarce or difficult to collect. At the same time, AI models are susceptible to data quality. If there is noise, mislabeling, or a data imbalance in the training data (too few samples of certain defect categories), it may affect the performance of the model and lead to inaccurate recognition results.

5.2. Intelligent Tool Selection and Disassembly Line Balancing

During the disassembly process, appropriate tools should be selected based on the type of connections. The connection methods of electric vehicle batteries include threaded connections, glue connections, welding connections, etc. Different connection methods correspond to different disassembly methods. AI can improve the efficiency of tool selection. Wang et al. [110] proposed a tool selection model based on a genetic algorithm (GA) to evaluate the suitability and matching value of disassembly tools in order to select the best disassembly tools. Liang et al. [111] constructed a mixed-integer, non-linear programming (MINLP) model of the multi-objective partial disassembly and line balancing problem (PDLBP) to achieve the minimization of the four optimization objectives of the number of workstations, workstation load, tool switching times, and energy consumption.

Disassembly line balancing (DLB) refers to the reasonable allocation and arrangement of disassembly tasks during the product disassembly process to improve disassembly efficiency, maximize economic benefits, reduce energy consumption, and balance the load of each station [112]. Traditional methods usually rely on engineers' experience and knowledge to manually configure and adjust the production line. Engineers assign tasks to different workstations based on the complexity of the task, process time, and resource availability. Engineers often use heuristic methods, such as the "longest processing time first" or the "shortest processing time first", to assign tasks through simplified rules in order to try to balance the working time of each workstation. AI can automatically analyze the tasks and resources of a production line, intelligently assign tasks to different workstations, and reduce the reliance on human intervention. This improves design efficiency, especially when faced with complex production lines. AI can quickly generate optimization solutions. At the same time, it can monitor the operating status of a production line in real time, dynamically adjust task allocation based on real-time data, and optimize the balance of a production line. This enables the production line to respond quickly to environmental changes, demand fluctuations, or failures. Ren et al. [113] proposed a mathematical model to solve the bi-objective disassembly line scheduling problem (Bi-DLSP) in order to optimize the total disassembly time and smoothing exponent. Wang et al. [114] applied the genetic simulated annealing algorithm to the disassembly line balancing problem. Yin et al. [115] used the Pareto-discrete hummingbird algorithm to address the disassembly line balancing problem. Experimental results showed that this method is more efficient in solving problems than the Discrete Artificial Bee Colony Algorithm (DABC), Hybrid Genetic Algorithm (HGA), Ant Colony Optimization Algorithm (ACO), and Hybrid Artificial Bee Colony Algorithm (HABC).

5.3. Intelligent Separation Optimization

During the battery disassembly process, the casing and module must be separated. Standard methods include mechanical cutting, laser cutting, hydraulic shearing, and manual disassembly. AI technology has great potential in modeling and optimizing laser beam processing quality characteristics, including geometric characteristics, metallurgical characteristics, surface quality, and the material removal rate [116]. Ding et al. [117] proposed an ensemble model based on a generalized regression neural network (GRNN) and Non-dominated Sorting Genetic Algorithm II (NSGA-II), which could be used to predict and optimize the quality characteristics of the fiber laser cutting of stainless steel. Pimenov et al. [118] reviewed modern approaches to cutting tool condition monitoring, particularly the application of sensors and AI technologies, demonstrating the potential of these technologies to improve machining accuracy, productivity, and tool life. Serin et al. [119] proposed collecting vibration, acoustic emission, current, and cutting force data through sensors and using deep learning methods for predictive and preventive maintenance.

6. Discussion and Future Prospects

This section discusses some possible directions for EVB disassembly.

6.1. Electric Vehicle Battery Swapping

Electric vehicle battery swapping stations are a new trend in electric vehicle charging. As shown in Figure 4 [120], when an electric vehicle is close to out of charge, the driver drives the car to a battery swapping station and directly replaces it with a fully charged battery, which is charged at the battery swapping station [121]. One of the drawbacks of electric cars compared to fuel cars is their weak range and long charging times. Even with fast charging, it takes about 30 min to reach 80% of full charge [122]. In contrast, the battery-swapping process takes about 3 min to reach a 100% state of charge (SOC) [123]. In addition to reducing the waiting time for electric vehicle users to charge, battery swapping stations can also independently plan the charging time, for example, charging the batteries at low peaks of electricity consumption, which helps reduce the economic cost of charging and maintain the stability of the power grid. Established in 2014, Nio has become a global intelligent EV company, with at least 30 battery swapping stations (BSSs) in Europe and 2200 stations globally.

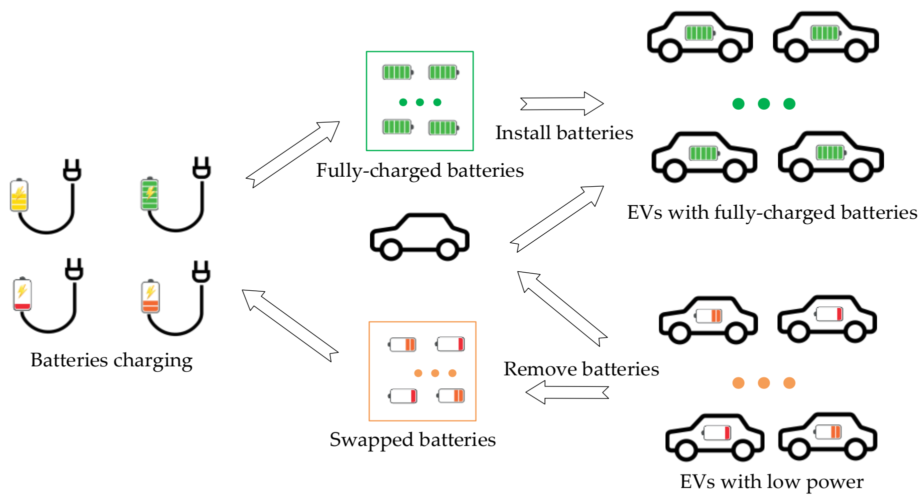

Figure 4. Process of battery swapping (adapted from [121]).

While battery swapping stations have certain advantages, there are still some current challenges faced:

- Only batteries of the same type and size can be replaced. However, the batteries of different car manufacturers worldwide, and even models of the same manufacturer, are not the same. This makes it impossible for battery swapping stations that serve cars from other manufacturers to be interoperable.
- Battery manufacturing costs account for a large part of the cost of electric vehicle production. Establishing a battery swapping station means manufacturing many additional batteries, which will incur relatively high expenses.
- To popularize battery-swapping, battery-swapping stations need to be widely established, which requires more investment than battery fast-charging stations. It also requires manufacturers to be able to integrate the supply chain. Due to great difficulties in this area, Tesla shifted its research and development direction from battery swapping to fast charging [124].
- The number of battery swaps also has peaks and troughs over time. For example, people generally drive during holidays, and the frequency of battery swaps for electric vehicles is currently higher. This causes problems with the layout of a battery swapping station and the reserve of replaceable batteries. The economic benefits will be low if

there are too many idle batteries. If there are too few replaceable batteries, the user must wait to charge their replacement battery.

- Consumers' psychological factors must also be considered. Battery replacement means that a car component is constantly being replaced, and some consumers may doubt this operating mode.

The rational layout and management of battery replacement stations are crucial to optimizing service coverage, and there is currently a series of research on the distribution optimization of battery replacement stations. AI-based methods can analyze real-time data, such as vehicle location, driving behavior, battery status, and battery swapping station capacity to optimize battery allocation. By predicting vehicle needs, AI-based methods can prepare a suitable inventory, reduce the waiting time, and improve battery swapping efficiency. AI-based methods can monitor the operation of all battery swapping stations in real time and dynamically adjust battery allocation and scheduling strategies. For example, when demand in an area surges, AI-based methods can automatically dispatch more batteries and resources to that area to cope with the peak demand. Yang et al. [125] proposed a data-driven BSS location optimization model using a one-month GPS trajectory dataset containing 514 EVs. Wang et al. [126] developed deep learning methods to predict EV battery swapping demand in order to optimize BSS arrangement. Yang et al. [127] developed an optimal battery allocation model for BSSs of EVs. This technology can be given priority in some large-scale vehicles, such as taxis. This technology will be more promising if various electric vehicle manufacturers can unify battery charging and discharging power and size for different models.

6.2. Intelligent Design for Disassembly (DFD)

Design for disassembly (DFD) simplifies the disassembly process [128]. DFD is a green manufacturing concept in which products are designed for ease of disassembly to recover valuable reusable materials and components and simplify maintenance through cost-effective separation. Therefore, by allowing the reuse, remanufacturing, and recycling of products, waste is reduced at the product's EOL. Traditional DFD usually adopts modular design, using standardized components and interfaces, so that different modules can be quickly identified and separated when the product is disassembled. Such a design simplifies the disassembly process and reduces the risk of damage to components. Based on traditional DFD technology, AI-based methods can help automatically generate optimized disassembly design solutions. At the same time, AI-based methods can take into account multiple design goals, such as minimizing the disassembly time, maximizing the material recovery rate, minimizing the cost, and providing optimal design suggestions to help designers find the best balance under multiple constraints. AI-based methods can also simulate the disassembly process through virtual simulation, predict problems that may be encountered in actual disassembly, and make improvements in the design stage. This predictive ability helps reduce design defects and improve product disassembly.

As shown in Figure 5, multiple intelligent DFD methods could be adopted. RFID and QR codes could be adopted during the manufacturing process to record information about EVBs, while processors and sensors could be placed inside the EVBs to monitor SOH conditions and estimate their RUL.

DFD is applied to make the components in a battery, such as the positive electrode, negative electrode, and electrolyte, more accessible for separation and recycling. Currently, recycling efforts are focused on cathode materials because these are the most economically valuable among retired LIBs [129]. Due to the graphite anode, an additional separation step is required. Anode-free batteries are a new trend that simplifies the disassembly process. Meanwhile, the anode-free battery, which removes excess lithium and combines a fully lithiated cathode with an uncoated current collector, can achieve the highest possible energy density [130]. Furthermore, this configuration saves costs, energy, and technical requirements associated with anode production, including slurry preparation, coating, and drying processes in the drying chamber [131]. The connection between each part can also be optimized to achieve non-destructive disassembly. Connected components and modules can be manufactured using shape-memory polymers, which offer the advantages of industrial feasibility, morphological diversity, and synthetic flexibility [132].

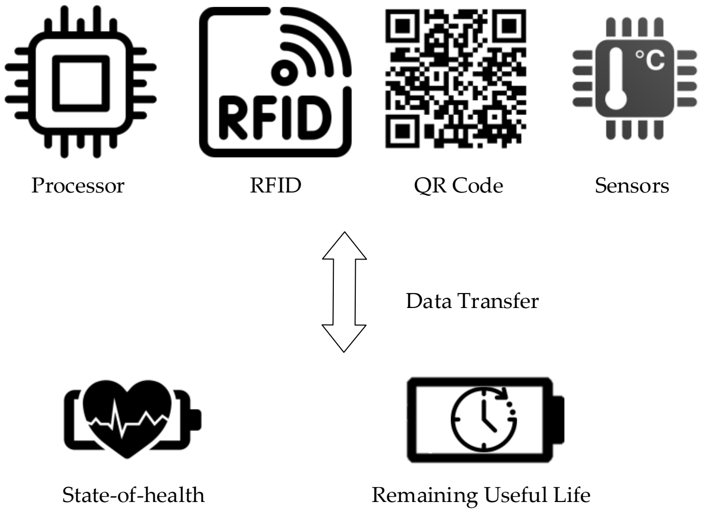

Figure 5. Multiple intelligent DFD methods.

6.3. Digital Twin and Human–Robot Collaboration Applications

The remote operation of the disassembly process can significantly improve its safety. Since toxic gases may be released during the battery disassembly process, improper operation may cause the risk of combustion and explosion. Digital twin (DT) and human–robot collaboration (HRC) are useful tools for realizing remote disassembly.

As shown in Figure 6, DT is achieved through a physical system with a virtual representation [133,134], and the digital model mirrors the physical system. Mirroring capabilities can be achieved through a data exchange, which requires installing sensors on the physical system to collect and transmit data over the network to the virtual model. At the same time, physical entities can also be operated using virtual models. Augmented reality (AR) is an excellent medium for achieving this function. AR is a technology that overlays computer-generated information or images onto the real world [135]. AR technology can combine virtual information with the natural environment using cameras, sensors, computers, and display devices. The use of DT and AR can realize remote control and reduce the difficulty of control, significantly reducing the safety risks of the working environment. It should be noted that the virtual model in the DT and AR needs to simulate the operating robot arm and the workpiece to be processed and the environment. Otherwise, the control that can be achieved on the virtual side may be restricted due to the operating environment on the physical side. In the past, the virtual end of digital twins generally used manual modeling; however, with the development of AI technology and the emergence of 3D point cloud technology, virtual models can be quickly modeled by scanning entities [136]. DT relies on a large number of sensors and data collection devices, which may involve the processing of sensitive information.

Due to the great difficulty of disassembling electric vehicle batteries and the small operating space in part of the disassembly process, which makes it difficult for the robotic arm to operate, it is difficult to automate the disassembly process [17] entirely. Human–robot collaboration (HRC) provides new ideas for disassembly by combining human intelligence and decision-making with the strength and precision of robots. For example, complex disassembly tasks are better suited to manual operations, while robots better handle hazardous and repetitive tasks. In traditional HRC, robots usually perform repetitive and precision-demanding tasks, while human workers are responsible for more complex tasks that require flexibility. The tasks in HRC disassembly are usually predefined, with little room for dynamic adjustment. AI-based methods can dynamically adjust task allocation based on real-time task complexity, worker status, robot capabilities, and other factors to ensure optimal collaboration between humans and robots. This dynamic allocation removes the limitations of fixed task allocation in traditional HRC. At the same time, AI-based methods give robots the ability to understand and respond to human natural language commands and gestures, making the interaction between humans and machines more intuitive and natural. Yuan et al. [137] proposed a new heuristic algorithm based on a multi-criteria assessment of human–robot collaboration. The proposed disassembly elasticity assessment method uses the fuzzy Bayesian-ANP-extension cloud model to convert human judgment into numerical values in order to help managers make better decisions. Guo et al. [138] proposed HRC partial destructive disassembly sequence planning (DSP) driven by multiple failures. The disassembly sequence is optimized through an improved genetic algorithm to improve the efficiency and automation of end-of-life product disassembly. Gao et al. [93] proposed HRC disassembly strategy optimization based on deep reinforcement learning. This approach enables each agent to choose a strategy that maximizes the overall gain, ensuring that humans and robots adopt optimal disassembly strategies. The challenge is that human workers may lack trust in AI-driven robots, especially when the AI's decision-making process is not transparent. Establishing and maintaining trust between humans and machines is an important challenge that needs to be achieved through reliable behavior and transparent decision-making processes.

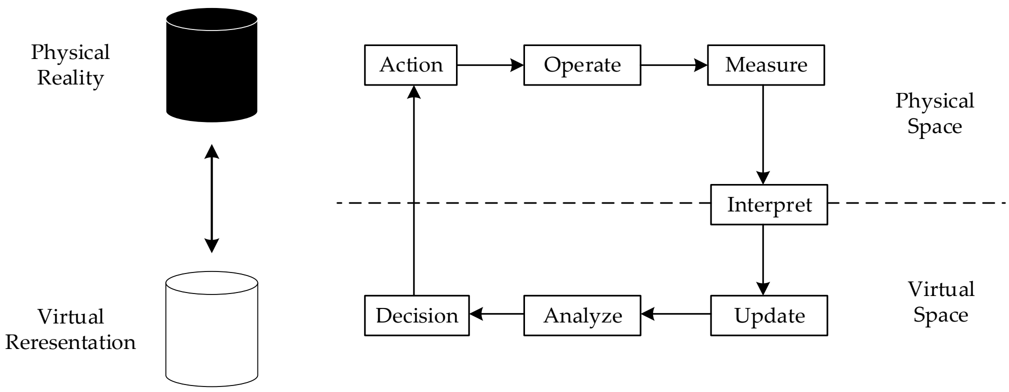

Figure 6. Digital twin implementation process (Adapted from [133]).

As shown in Figure 7, disassembly tasks' classification is performed to determine the disassembly sequence for batteries and the characteristics of parts in batteries. The second step is to allocate disassembly resources to determine the tasks allocation in HRC. After that, the entire process will be integrated into a solution, and the solution will be evaluated.

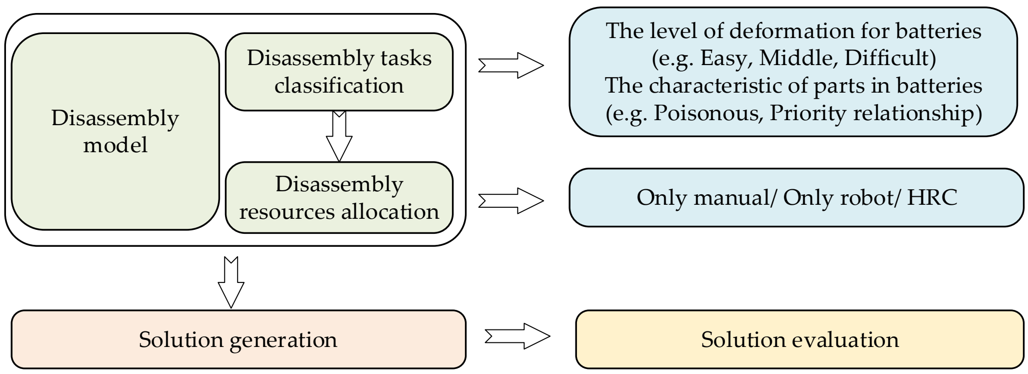

Figure 7. Flow chart of human–robot collaboration (adapted from [95]).

Since humans and robots will operate in the same environment, the robot may harm humans during movement, and safety factors must be considered during operation. Xu et al. [139] proposed a strategic disassembly information model. This method used the improved discrete bee algorithm to solve the HRC disassembly line balancing problem. Liu et al. [140] proposed a collision-free HRC system based on context awareness. The system can plan the robot's path to avoid collisions with human operators while reaching its target location promptly and recognize human operator gestures with low computational overhead, further improving assembly efficiency. Wang et al. [141] proposed a deep learning-enhanced DT framework in HRC manufacturing. The proposed framework significantly improves the security and reliability of the HRC system through deep learning technology.

6.4. Charging Optimization

Changes in the voltage, current, temperature, etc. during charging will also affect battery life. Improving charging parameters to extend battery life saves energy and protects the environment. At the same time, compared with fuel vehicles, electric vehicles have significant disadvantages, namely a slow charging time and low endurance. Electric cars will be further promoted if the charging rate can be improved.

Battery aging can be divided into cyclic aging and calendar aging. Cyclic aging occurs during charging and discharging, while calendar aging occurs when a battery rests [142]. The temperature during charging, including the ambient temperature and the heat generated during battery charging, impacts the battery life. Park et al. [142] proposed a model and showed that indoor charging stations can reduce battery aging management costs by up to 13.31% compared with outdoor charging stations. Chung et al. [143] investigated battery maintenance during extended periods of inactivity. They designed an optimal charge profile that maintains battery status under ideal conditions to minimize degradation during idle periods while still meeting charging energy requirements.

There is currently much research on fast charging. Wang et al. [144] proposed a multi-stage charging strategy based on a fractional-order model using the Moth–Flame Optimization (MFO) algorithm. The test showed that each fitness function part's current stage number, cut-off voltage, and weight significantly affect charging performance. The fitness function should be weighted differently based on specific requirements. Jiang et al. [145] proposed a fast-charging design based on Bayesian optimization. They explored three acquisition functions (i.e., expected improvement, improvement probability, and lower confidence bound) to minimize the charging time for single-step and multi-step constant-current charging profiles. However, fast charging often accelerates battery aging. AI-based methods can provide an innovative approach to optimizing the balance between fast charging and reducing battery aging. The voltage and current of the traditional charging method are constant. An AI-based system can monitor the battery's charging status (such as voltage, temperature, charging current, etc.) in real time and dynamically adjust the charging rate based on these data to optimize charging efficiency and prevent the battery from overheating. At the same time, charging data can also be used for battery state-of-health estimation. However, the challenge is that existing charging hardware and infrastructure may not be fully compatible with the needs of AI-based systems. In order to achieve AI-driven fast charging, existing hardware may need to be upgraded or modified, which may involve high cost.

7. Conclusions

With the popularity of electric vehicles, disposal of retired electric vehicles is being considered. The traditional metal extraction method of crushing retired electric vehicle batteries destroys their structure and can only facilitate recycling of raw materials, which is inefficient. One optimization method is to conduct SOH estimation on electric vehicle batteries. Batteries with SOH values lower than 80% but higher than 50% can be used for echelon utilization. They are systematically disassembled if the SOH value is lower than 50%. AI has excellent potential in EV battery disassembly. To evaluate AI applications in the EVB disassembly process, this survey has provided a more systematic summary of AI applications in EV battery disassembly, including SOH estimation, disassembly sequence planning, and disassembly operations. The article has also discussed promising development directions in battery recycling, including battery swapping, intelligent design for disassembly, DT and HRC, and charging optimization. Further research in these areas is needed. Overall, this review has provided a systematic summary of AI in EVB disassembly and pointed out possible directions for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

ACO	Ant Colony Optimization Algorithm
AI	Artificial intelligence
AR	Augmented reality
BMS	Battery management system
BSSs	Battery swapping stations
CNN	Convolutional neural network
DABC	Discrete Artificial Bee Colony Algorithm
DFD	Design for disassembly
DNN	Deep neural network
DSP	Disassembly sequence planning
DT	Digital twin
EIS	Electrochemical impedance spectroscopy
EOL	End of life
EVB	Electric vehicle battery
EVs	Electric vehicles
GA	Genetic algorithm
GRNN	Generalized regression neural network
HABC	Hybrid Artificial Bee Colony Algorithm
HGA	Hybrid genetic algorithm
LIBs	Lithium-ion batteries
LSTM	Long short-term memory
MFO	Moth–Flame Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
PNt	Petri Net
RES	Rotating edge similarity algorithm
RF	Random forest
RUL	Remaining useful life
SOC	State of charge
SOH	State of health
SVM	Support vector machine
TL	Transfer learning

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