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Review

# A Review on Dynamic Recycling of Electric Vehicle Battery: Disassembly and Echelon Utilization

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**Abstract:** With the growing requirements of retired electric vehicles (EVs), the recycling of EV batteries is being paid more and more attention to regarding its disassembly and echelon utilization to reach highly efficient resource utilization and environmental protection. In order to make full use of the retired EV batteries, we here discuss various possible application methods of echelon utilization, including hierarchical analysis methods based on various battery evaluation index. In addition, retired EV battery disassembly is also reviewed through the entire EV battery recycling based on human–robot collaboration methods. In order to improve the efficiency and reduce the cost of EV recycling, it is necessary to find a suitable recycling mode and disassembly process. This paper discusses the future possibility of echelon utilization and disassembly in retired EV battery recycling from disassembly optimization and human–robot collaboration, facing uncertain disassembly and echelon utilization.

**Keywords:** electric vehicle battery; disassembly; echelon utilization; disassembly optimization; human–robot collaboration disassembly

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**Citation:** Xiao, J.; Jiang, C.; Wang, B. A Review on Dynamic Recycling of Electric Vehicle Battery: Disassembly and Echelon Utilization. *Batteries* **2023**, *9*, 57. https://doi.org/10.3390/batteries9010057

Academic Editors: Liang Gao, Akhil Garg, Wei Li, Matthieu Dubarry and Carlos Ziebert

Received: 23 October 2022
Revised: 5 January 2023
Accepted: 10 January 2023
Published: 12 January 2023



## 1. Introduction

With the increasingly prominent contradiction between human development and resource utilization, electric energy, as a kind of clean energy, has attracted more and more attention regarding environment protection and green manufacturing development. In recent years, electric vehicle (EV) batteries have received strong support from various countries all over the world, causing the sale volumes of EV batteries to keep increasing under various national policies [1,2]. The phenomenon can be observed obviously with global electric vehicle sales reaching 16.5 million in 2021, reaching nearly 10% of the automotive market [3]. According to the Swedish industry consulting company, the global LIB market demand will reach CNY 99.98 billion by 2025, with shipments reaching 439.32 GWh and EV batteries reaching 253 million by 2030 [4]. In China, the number of EV batteries in the energy market is predicted to have a dramatically increasing trend from 2013 to 2030 [5]. Moreover, it can be predicted that the rapidly growing trend will be continue to increase in the future and will reach 145 million by 2030 [6]. By comparing various power batteries (e.g., Pb-Acid, Ni-MH, Ni-Cd, Li-ion battery, graphene-based battery, all-solid-state battery, etc.) [7–10], various performances can be described as shown in Table 1. Due to the excellent performance in the actual application, such as energy efficiency and cycle times, Li-ion batteries have become the mainstream of EV batteries [11]. Although next-generation batteries have shown remarkable properties in individual ways, their high cost and toxicity, as well as the low availability of materials, limit their large-scale use before they are widely used in cars or transportation devices [12,13].

However, the Li-ion battery for electric vehicles or devices will be recycled when the remaining capacity is reduced to 70–80% of the origin capacity [14], and the service life of EV batteries is about 6–8 years [15]. Considering the growing application trend of EVs, retired EV batteries will gradually appear on a large scale in the future, and it will reach

117 GWh and 280 GWh in 2025 and 2030, respectively [16]. Although retired batteries have a limited service life in actual applications, they still have enough residual energy and reuse possibility to support their continued works in other scenarios (e.g., energy storage, low-power EVs, etc.) [17] and can be used to recycle a large number of precious metal elements [18,19]. Therefore, the research on the recovery and reuse of retired EVBs not only provides a possibility of environment protection and resource savings [20], but also enables the cost reduction of the battery to create more value products [21]. The echelon utilization of EV batteries and the recycling of resources can be regarded as a potential application to enhance the economic and environmental benefits of retired EV batteries and to achieve sustainable energy development [22]. There are two major application scenarios for echelon utilization: static energy storage stations and dynamic mobile charging applications. A typical static scenario is an energy storage station to provide the energy storage for the power generation, such as charging stations, communication base stations, etc. Dynamic recycling utilization can be usually implemented in mobile charging cars, low-speed EVs, and other applications with lower performance requirements [23].

**Table 1.** Comparison of the performances of various power batteries [10].

| Battery Characteristics | Lead Acid | NiCd | NiMH | Li-Ion | All-Solid-State Battery | Graphene-Based Battery |
|---|---|---|---|---|---|---|
| Normal voltage (V) | 2.0 | 1.2 | 1.2 | 3.6 | / | / |
| Specific energy (Wh/kg) | 30–50 | 45–80 | 60–120 | 100 | 200–500 | 600 |
| Specific power (W/kg) | 130 | 200 | 250 | 330 | / | >600 |
| Energy efficiency (%) | 65 | 80 | 85 | 95 | / | / |
| Cycle life (times) | 200–300 | 500–1000 | 300–500 | 1000 | 2000~3000 | >1000 |

In addition, the fundamental structure of the EV battery can a battery pack consisting of several battery modules, and a battery module consists of a number of battery cells [24]. Currently, there are two main technical methods for echelon utilization: cell level and module level. Different retired batteries have different standards in regard to their production and manufacturing process, and they work in different work environments and usage habits, which will cause the retired batteries to be inconsistent in regard to various design parameters and their performance index [25]. The inconsistency of the battery makes it impossible to make a broad judgment on all batteries. Different batteries have different performance parameters, and this affects their echelon utilization scenarios. Different sizes of retired EV batteries cannot use fixed disassembly actions. Therefore, it is necessary to explore the internal characteristics of retired EV batteries, including their capacity, state of charge (SOC), internal resistance, and self-discharge, within the same batch of battery cells [26]. The echelon utilization needs to consider the inconsistencies of the battery efficiently at various application scenarios [27].

A retired EV battery consists of a battery module, frame structure, high-voltage wiring harness, battery management system (BMS), cooling system, and other modules. Its complex structure makes it impossible for direct use in echelons or recycling. Therefore, it is necessary to utilize many disassembly tools to accomplish the entire disassembly battery pack into the battery module or battery cells for a specific scenario. Thus, retired EV battery disassembly plays a pivotal role in the echelon utilization and recycling of EV batteries [28]. EV battery disassembly into modules or cells also corresponds to two types of echelon utilization: module-level utilization and cell-level utilization. Due to the uncertainty of the EV battery modules, it is still dominated by battery cell-level disassembly. Battery disassembly is a technical and dangerous task for workers. For some retired EV batteries with unknown performance properties, wrong operation can lead to electrolyte leakage, corrosion, insulation damage, overheating, and even explosion [29]. Therefore, it is necessary to envisage the use of robots to automatically disassemble the battery according to the different physical structures, battery types, and parameter performances of the battery to solve the safety problem of battery disassembly and improve its efficiency. Nowadays, the mainstream battery disassembly still uses a semi-automatic disassembly method: the robot implements some simple and repetitive disassembly actions facing with uncertain product quality and category, such as screw tightening [30]. Thus, it is necessary to complete the automatic disassembly based on the uncertainty of the battery as an open issue, and we discuss its related research.

## 2. Current Challenges of Battery Echelon Utilization and Disassembly

Battery manufacturing and production can be used to design its structures and parameters based on various application methods. The battery packs on the current battery market have different structures and assembly methods of the battery modules from the battery packs, including battery types and battery chemical properties [31]. The diversity of EV batteries makes it a major challenge to disassemble them into battery modules or cells. As shown in Table 2, different modules have stipulated different physical dimensions and structures, which require us to find out different disassembly strategies. However, different structure dimensions and sizes might cause huge challenges to the entire automation of the disassembly process.

**Table 2.** GB/T 34013–2017 electric vehicle various battery module dimensions.

| Various Battery Module Types | Length (mm) | Width (mm) | Height (mm) |
|---|---|---|---|
| #1 | 211–15 | 141 | 211/235 |
| #2 | 252–590 | 151 | 108/119/130/141 |
| #3 | 157 | 159 | 269 |
| #4 | 285–793 | 178 | 130/163/177/200/216/240/255/265 |
| #5 | 270–793 | 190 | 47/90/110/140/197/225/250 |
| #6 | 191–590 | 220 | 108/294 |
| #7 | 547 | 226 | 144 |
| #8 | 269–319 | 234 | 85/297 |
| #9 | 280 | 325 | 207 |
| #10 | 18–27, 330–672 | 367 | 114/275/429 |
| #11 | 242–246 | 402 | 167 |
| #12 | 162–861 | 439 | 363 |

The disassembly of EV batteries mostly depends on manual-involved disassembly by technical workers, owing to the complexity of uncertain disassembly objects. Considering the voltage and weight of EV batteries in the disassembly operations, the disassembly workers should have high technical requirements to accomplish the professional operations with special disassembly tools. As known, there are many huge challenges faced by the industrial disassembly production line, considering that there are few skilled workers. For example, there are only 1000 technicians trained to disassemble electric vehicles in the UK, with another 1000 being trained. Untrained technicians repairing electric cars can have many missing operations, causing some risks to recycling EV batteries. Similarly, in many countries with high labor costs, manual disassembly is uneconomic for material extraction and manual-operation recycling [32]. Germany has increased investment in the construction of electric vehicle manufacturing plants in China with the rapidly increasing volume of EV batteries, making the efficiency of manual disassembly difficult to realize such a large workload of massive disassembly tasks. However, it is necessary to balance the economics of the disassembly process and the safety of disassembly operations in the actual disassembly applications. In order to improve the automation level of disassembly remanufacturing, it is possible to combine the robot and human operation to accomplish the higher-efficiency disassembly tasks, thus ensuring a less time-consuming recycling process. However, there are many challenges to battery pack and module disassembly:

- Different modules have different physical structures and performance parameters, which require us to consider different disassembly processes and strategies with disassembly uncertainty.
- With the volume of retired EV batteries under a huge requirement context, the number of recyclable EV batteries is also increasing, which greatly increases the workload of EV battery disassembly. Therefore, it is necessary to improve the efficiency of disassembly in the EV battery recycling.
- The safety of disassembling operations for EV batteries makes it difficult to reasonably plan the disassembly process and strategy and optimize appropriate disassembly planning tasks for the retired EV batteries.

The echelon utilization of EV batteries includes the reuse of battery modules and battery cells, which can be used in various application scenarios. Usually, the disassembled battery can be analyzed to accomplish the different hierarchical applications of echelon utilization by considering the remaining performance of EV battery modules or cells [33]. After the EV battery meets the retired requirements, due to the fact that the battery cell itself has initial inconsistency in the manufacturing process [25], it is necessary to consider the different working environment to accomplish the consistency of the new reorganizing battery products. The characteristics of the retired battery need to be analyzed for further classifications and reorganizations, including battery capacity, internal resistance, self-discharge rate, remaining useful life (RUL), lithium plating, solid electrolyte interphase (SEI) film thickening, electrolyte reduction, etc. However, we need to determine the health status of the retired EV battery to enable the accurate and efficient echelon utilization by considering the internal characteristics and preformation of disassembled pack modules or cells. For the echelon utilization of the retired battery, due to the dangerous possibility of the lithium-ion battery itself and the deterioration rate of the battery, the safety and residual value of the battery need to be tested urgently before echelon utilization [34]. The historical data of batteries are usually missing or fragmented, thus making it difficult to accurately evaluate the health and residual value of retired batteries. The historical data storage method of the battery needs to be improved and adjusted so that the subsequent battery echelon utilization can be carried out correctly and efficiently [35,36].

The echelon utilization of battery recycling is accompanied by disassembly, classification, and reorganization, which require a lot of labor costs and material resources that affect their economic and environmental benefits with respect to the specific industrial recycling requirements. Considering various types of battery cells with their anode materials and chemical properties, different strategy methods for echelon utilization will affect the overall efficiency of battery recycling. In addition, the echelon utilization of retired EV batteries has huge challenges relating to the recycling methods and specific technology:

- Owing to the uncertainty of the application environment and scenario modes, the specific parameters of the retired EV battery cannot be accurately evaluated to determine the specific echelon hierarchy.
- The retired EV batteries will decay and age at a faster rate for echelon use, making it difficult to guarantee the continuity of battery echelon utilization. The retired EV batteries need to be evaluated by their parameters and performance before the specific echelon applications with safety analysis during the entire recycling process.
- It is also necessary to balance all recycling stages to support the optimal application scenarios based on the analysis of disassembly, classification, and even energy consumption.

## 3. Related Policies and Technical Standards for Echelon Utilization

Echelon utilization enterprises should meet the requirements of the industrial specification in comprehensive echelon utilization for EV batteries. In order to support the intelligent remanufacturing of EV battery recycling, we should consider giving priority to the echelon utilization of EV batteries at the pack level or module levels. The disassembly of battery packs or modules is in line with the relevant requirements of the specification for

EV battery recycling, echelon utilization, and disassembly (GB/T33598). Echelon utilization enterprises are encouraged to extend possible echelon products that are suitable for signal base stations, energy storage, charging and replacement, and other fields. New energy EV battery manufacturers and other enterprises are encouraged to negotiate and share the factory's technical specifications information, charging rate information, and monitoring data information (voltage, temperature, SOC, etc.) for echelon utilization battery enterprises. Echelon utilization enterprises carry out battery performance tests in accordance with relevant standards such as the Vehicle Power Battery Recycling and Utilization Residual Energy Detection (GB/T34015) and evaluate the residual value of retired EV batteries by combining actual test data to improve the efficiency of echelon utilization that provides enough service performance, reliability, and economy of echelon products. Electrical insulation, thermal management, battery management, and other factors should also be considered in the design of echelon products to ensure the reliability in the EV recycling products. The echelon products shall be verified by performance tests and their electrical performance, it is easy to meet its safety and reliability through the relevant standards and requirements of the application field, as shown in Tables 3 and 4. The echelon products shall be marked with commercial information code according to the Code Rules for Automobile Power Batteries (GB/T34014). Its related information, such as normal capacity, normal voltage, name, address, production place, and traceability code of the echelon products, shall be marked on the echelon product label, and the original EV battery code shall be compared as well.

**Table 3.** International standards for related echelon utilization and disassembly recycling.

| Relevant Standard | Corresponding Resources | Issuing Country or Organization |
|---|---|---|
| Safety operation requirements and tests of secondary lithium batteries | JIS C 8715-2:2019 | Japan |
| Safety requirements of secondary lithium battery for light electric vehicle | EN 50604.1.2016 | Europe |
| Security Testing in Special Scenarios | ISO 12405.1 | International Organization for Standardization |
| Square cell circular battery in secondary battery | IEC 61960 | IEC |
| Reliability and abuse testing | IEC 62660.2 | IEC |
| Recycling and disassembly | VDI 2343 Sheet 3 | Germany |

**Table 4.** Related standards for echelon utilization in EV batteries (in China).

| Relevant Standard | Corresponding Resources |
|---|---|
| Retired battery appearance requirements | GB/T 34015.3-2021 Part 5.1 |
| Echelon Utilization Application Scenario for Vehicle Battery | GB/T 34015.3-2021 Part 5.2.1 |
| Echelon Utilization Application Scenario for Energy storage batteries and other applications | GB/T 34015.3-2021 Part 5.2.2 |
| Not suitable for echelon utilization | GB/T 34015.3-2021 Part 5.2.3 |
| Cycle life requirements | GB/T 34015.3-2021 Part 5.3 |
| Safety demand | GB/T 34015.3-2021 Part 5.4 |
| Product requirements for echelon utilization | GB/T 34015.3-2021 Part 6 |
| Residual energy detection requirements | GB/T 34015-2017 Part 5 |
| Detection process specification | GB/T 34015-2017 Part 6 |
| Specific detection methods | GB/T 34015-2017 Part 7 |
| Related terms and detection parameters | GB/T 31486-2015 |
| Battery disassembly industry requirements | GB/T 33598-2017 Part 4 |
| Disassembly process | GB/T 33598-2017 Part 5 |
| Disassembly separation removal process | GB/T 34015.2-2020 |
| Recycling packaging transportation specification | GB/T 8698. 1-2020 |
| Battery information collection | GB/T 34014-2017 |
| Specification size of battery products | GB/T 34013-2017 |

Echelon utilization can prolong the service life of the retired EV batteries, as this can make the retired EVBs create more economic profits to reduce the initial product cost and ensure the sustainable recycling market. Lih et al. [37] discussed the potential echelon utilization value of EVBs that can be used to explore the relationship between battery life and recycling benefits. Mahyar et al. [38] studied the economic evaluation of lithium-ion battery pack recycling in residential, industrial, and photovoltaic power application aspects from users and the government that further explained the economic benefits of echelon utilization in the field of energy storage. Martinez-Laserna et al. [33] presented a comprehensive review of the literature that analyzed the concept of the second-life battery from the perspective of economic, technical, and environmental feasibility. As shown in Table 5, the application scenarios of echelon utilization include static and dynamic recycling scenarios, which find out the optimal recycling method based on the optimization algorithms for the specific retired EV battery. The reuse of the retired EV battery in specific scenarios can effectively reduce the possible degradation and iteration speed of EV retired batteries. Most static application scenarios are mainly applied on some energy storage systems that can be used in communication base stations, building energy storage, and microgrids [39]. Guo et al. [40] proposed the utilization of thermal energy storage system for a second-life battery to find out the optimal planning model that can be used to demonstrate the economic effectiveness and service-life improvement of the retired EV batteries. Chiang et al. [41] developed a converterless energy management system to control energy flow that can assess various EV batteries by analyzing the monitoring voltage of the battery pack. Hussam et al. [42] designed a microgrid of batteries to provide energy storage support by a fuel cell-battery that presented battery-life balancing solutions by new framework of balancing the battery utilization. In the practical use of the battery, the cost and the reliability of the battery's secondary use will have a feasibility impact [43]. The uncertainty of the battery performance is mainly manifested by the increasing possibility of unbalanced capacity of the battery pack after the retired battery modules or cells are assembled together, which will result in increasing the risk of over voltage and/or over current within a battery pack to make it difficult to support well-integrated battery management [39]. The economic-benefit analysis of battery echelon utilization usually needs to establish a cost–benefit model considering multiple factors according to the related application scenarios and analyze the economic benefit under the related policies [44]. The dynamic application scenarios of retired batteries are mainly applied on some low-speed vehicles, such as electric bicycles, low-speed scooters, logistics vehicles, and urban sanitation vehicles [45]. The echelon utilization of batteries in EV battery resource recycling is collectively regarded as an economic recycling utilization method, which can generate both economic and environmental benefits to achieve sustainable development [46].

**Table 5.** The application scenario of echelon utilization.

| Echelon Utilization | Possible Potential Commercial Opportunity | Ref. |
|---|---|---|
| Static application scenarios | Park-level integrated energy stations | M. Guo et al. [40] |
| | Converterless energy management system | Y. H. Chiang et al. [41] |
| | Microgrid battery group | Y. Gao et al. [47] |
| | Solar energy storage system | Y. Al-Wreikat et al. [48] |
| Dynamic application scenarios | Electric bicycles | J. Zhu et al. [45] |
| | Low-speed scooters | H. Ambrose et al. [49] |
| | Urban sanitation vehicles | X. Lai et al. [14] |

However, it is necessary to disassemble and reassemble the battery before echelon utilization of retired EV batteries, and this is usually called the remanufacturing process. Remanufacturing is defined as the process of rebuilding parts and components from used products [50]. The remanufacturing process permits the product to be even the same as the original product in terms of quality, performance endurance, and warranty, and it can greatly reduce energy consumption and production cost when compared with general manufacturing [51]. Both the remanufacturing and recycling of EV batteries always mainly focus on the disassembly process that is generally considered to optimize the disassembly task for retired EV batteries. However, the recycling process of retired EV batteries is a technological combination of physical separations and chemical extraction. The first step is the physical separation that disassembles the battery packs into battery modules or cells to facilitate the subsequent chemical recycling stage. The first step in the recycling process of retired EV batteries needs to pre-evaluate the aging degree of the batteries and analyze the recycling method before disassembly. Then it is necessary to discharge the retired EV batteries that can ensure the following safe disassembly operations. Physical separation can better acquire the refined cells to ensure a better chemical reaction and recycling rate. The chemical extraction aims to acquire the precious metal resources such as Li, Co, and Ni from the retired EV batteries, which can regenerate lithium iron raw materials.

The disassembly process has huge effects on the whole process of the echelon utilization and recycling process, which is an indispensable step in the remanufacturing process to acquire the valuable components or even find materials. It is necessary to re-evaluate the disassembly tasks according to the conditions and quality of EV batteries to accomplish the disassembly operations of checking, testing, and sorting [52]. The characteristics of retired the EV battery need to evaluate its state of health (SOH), state of charge (SOC), and remaining useful life (RUL) by considering its complexity and diversity of multilevel structure [53]. The evaluation of EV battery recycling is important to determine the final disassembly feasibility that needs to balance the possibility of disassembly operations and the disassembly cost [54]. In order to achieve a better disassembly task in EV battery recycling, some reasonable detection methods have emerged to quickly and accurately check, test, and sort them, as shown in Table 6. A widely used recycling technology method for industrial checking and recognition needs to acquire the labeling information for the EV battery [55], which can effectively track the battery to obtain the specific battery information by open data-sharing support [56].

**Table 6.** Related research points for echelon utilization for EV battery.

| Echelon Utilization | Ref. | Side Reaction | High Efficiency | Safety Index | Performance Index | Aging and SOH |
|---|---|---|---|---|---|---|
| Estimation and evaluation | Harlow et al. [57] | √ | | | | |
| | Santhanago et al. [58] | √ | | | | |
| | Santos-Mendoza et al. [59] | | | | √ | |
| Sorting and regrouping | Sheikh-Zadeh et al. [60] | | | √ | | |
| | Xin et al. [61] | | √ | √ | √ | |
| | Guo et al. [62] | | | | √ | √ |

The prediction of the state of charge (SOC) data can be analyzed by a variety of time-dependent factors, such as external temperature, charge and discharge rates, and battery pack aging. Currently, the SOC detection methods mainly include the open-circuit voltage method, Kalman filter algorithm [63,64], and neural network method [65,66]. Kawahara et al. [67] combined SOC based on open-circuit voltage with SOC to obtain accurate charge states that can adjust battery characteristic parameters by simple analysis. Wu et al. [68] used electrochemical impedance spectroscopy (EIS) to detect the SOC of lead–acid batteries under different conditions. In order to solve the problems of low SOC prediction and charge-state estimation, Zhang et al. [69] proposed an intelligent algorithm model to predict the low SOC that combined the genetic algorithm (GA) and echo state network (ESN) to reduce the error within 4%. It is necessary to have a pre-inspection on the retired EV batteries to evaluate their aging degree, which can be used to determine the optimal recycling process for retired EV batteries [70].

The state of health (SOH) is commonly used as an estimation index to evaluate the battery-aging degree, as shown in Figure 1, which is easily affected by characteristic parameters of the battery, including operation temperature, depth of discharge (DOD), discharge current [71], state of charge (SOC), and cycling depth, as well as charge throughput [72].

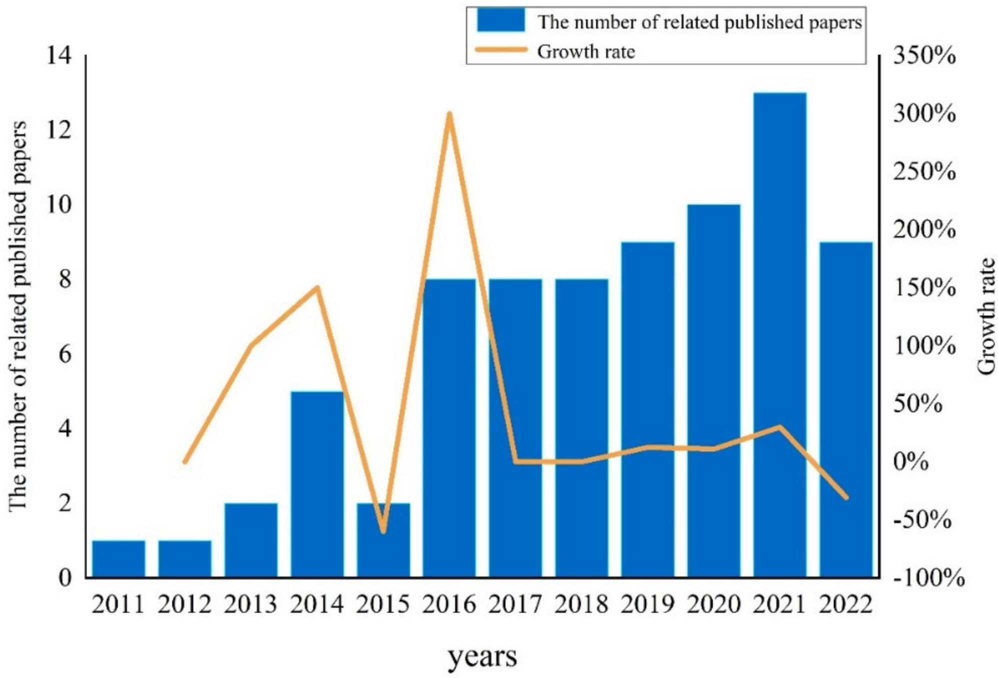


**Figure 1.** Statistics of related papers on the estimation of the SOH of EV battery.

The battery can be used for a certain period that its internal characteristics mainly manifest as capacity attenuation [73]. The battery capacity can present the current maximum capacity of the battery, which is different from the initial capacity, in order to analyze the its performance; namely Incremental Capacity Analysis (ICA) [74–76], Electrochemical Impedance Spectroscopy (EIS) [77–79], X-ray computed tomography (CT) [80], and other technologies based on the physical and chemical properties of the battery can be used to obtain the parameters required by evaluating the battery-aging degree. EIS has been widely used in battery-aging analysis in recent years due to its high accuracy and non-invasiveness. EIS uses a low-amplitude sinusoidal current or voltage signals to excite the EV battery within a certain range to obtain a change in impedance [81]. The surface layer model (divided into high-frequency, medium-frequency, and low-frequency regions) is commonly used to represent the extraction and insertion process of lithium ions in the chimeric electrode. The measured EIS spectrum is divided into high-frequency, medium–high-frequency, medium-frequency, and low-frequency regions. The electronic conductivity of the active material affects the medium–high frequency region, corresponding to the surface-film resistance [82]. The main step of the charge–discharge process is the extraction and insertion of lithium ions in the positive- and negative-electrode materials. Diffusion coefficients of positive and negative electrodes have an intuitive representation. The ion diffusion coefficient affects the low-frequency region, corresponding to the charge transfer resistance at the electrode/electrolyte interface. In addition, quantitative or semi-quantitative analysis of electrochemical impedance spectroscopy data allows for the extraction of kinetic information of the electrode processes in batteries. Surface film resistance and charge transfer resistance are the key factors affecting the battery charge and discharge performance, and they can also be used to determine the degree of battery aging [83].

Waldmann et al. [84] discussed the application methods above and reviewed the disassembly optimization methods for retired EV battery cells. By considering the characteristics of SOH as an indicator, we can divide the echelon utilization of retired EV batteries into four application stages. The first stage is that the capacity of battery SOH is in the range of 100%~80%, which can fully meet the traction application for EVs [85]. When the SOH of the battery drops below 80%, it should no longer be used for EVs, for safety reasons, that are mainly used in the field of energy storage, such as the standby power supply of communication base stations [86] and photovoltaic power storage equipment [47]. If the SOH is below 50% and above 40%, it applies to the third stages that are mainly used for other low-end users, such as electric motorcycles. However, it is important to accurately estimate the SOH of the battery that is a prerequisite to estimate whether the battery is suitable for echelon utilization or regenerative material recycling. As is known, it is necessary to discharge the fully charged lithium-ion battery and measure the total amount of discharged electricity to obtain the SOH. However, this original method is time-consuming and energy-consuming, which is unreasonable in practical application. Therefore, it is necessary to comprehensively analyze the internal and external characteristic parameters of the lithium-ion battery and establish the health-state estimation model of the lithium-ion battery.

The methods of SOH estimation and RUL prediction can be divided into a model-based method and data-driven method, as shown in Table 7. The aging estimation method is to establish the corresponding evaluation and prediction model by revealing the physical and chemical mechanism of battery aging, mainly including the electrochemical method and equivalent circuit method. The electrochemical method is based on the internal and external characteristics of the battery to analyze the actual aging mechanism of the battery by simulating the aging process of the battery, which can be used to establish a mathematical model. Andrew et al. [87] presented the systems of microscopically reversible reactions, including both heterogeneous thermal reactions and electrochemical charge-transfer reactions. Meyer et al. [88] proposed the transfer processes and charge-transfer reactions in a five layered single cell consisting of current collectors, electrode layers, and separator by Comsol Multiphysics simulation. Liu et al. [89] presented an adaptive nonlinear observer design that compensates nonlinearity to achieve better estimation accuracy. Although the electrochemical model has complete theory and high accuracy, there are complex mathematical equations, which make it difficult to solve the external environmental factors. An equivalent circuit model [90] is constructed by using circuit elements to simulate the dynamic characteristics of the battery based on the working principle of the battery that its accuracy is slightly lower than that of the electrochemical model with the simple structure and data analysis. Although the model-based method can provide high prediction accuracy, it often needs a high understanding of the battery aging mechanism [59]. The data-driven method does not require researchers to have a lot of relevant professional knowledge, but it trains an approximator through a large number of data sets to map the relationship between input and output, including the random filter algorithm, time series analysis approach, regression analysis methods, and machine learning [91]. The random filtering method is usually used to predict the current battery condition combined with the empirical model of battery degradation. Therefore, it is popular to predict their related performance by model-driven methods in many works of the literature, including the particle filter (PF), unscented particle filter (UPF), extended Kalman filter (EKF), and unscented Kalman filter (UKF).

However, the implementation of this method can be summarized by analyzing the degradation characteristics, extracting the degradation silver, and predicting the remaining life. The empirical model can be used to describe the battery degradation process by extracting health indicators (HIs) from experimental data and fitting the experimental data. Cheng et al. [92] presented the effects of different storage temperatures and storage times on battery capacity degradation, which established a semi-empirical model to predict the remaining life according to the residual capacity degradation. Dalal et al. [93] presented the detailed implementation of a lithium-ion battery life prognostic system, using a PF framework. Zheng et al. [94] proposed a new method to predict battery short-term capacity by using an unscented Kalman filter (UKF) and correlation vector regression to RUL. Zhang et al. [95] proposed an improved unscented particle filter (IUPF) method based on Markov chain Monte Carlo (MCMC) for RUL prediction of Li-ion battery. Noise often has a great impact on the prediction results, but this method does not consider the noise components. However, a time series and regression analysis can solve these problems. Liu et al. [96] introduced an optimized nonlinear degradation auto-regressive (ND-AR) time series model for remaining useful life (RUL) estimation of lithium-ion batteries. Zhou et al. [97] proposed a novel approach for RUL prognostic which combines empirical mode decomposition and autoregressive integrated moving average (ARIMA) model. Selina et al. [98] proposed the effects of different working conditions and ambient temperature under constant discharge current on the remaining life of the battery based on a data-driven Bayesian prediction model. Kai et al. [99] predicted the battery impedance based on a GPR algorithm to indirectly infer the remaining capacity and remaining life. Sarasketa et al. [100] considered the effects of different DODs, ambient temperatures, and charge–discharge current ratios on cycle life by establishing a semi-empirical dynamic model to study the parameters of the battery to predict the cycle life of the battery.

**Table 7.** Comparing various methods for SOH estimation and RUL prediction.

<table>
<tr><th></th><th colspan="2">Modeling Methods</th><th>Description</th><th>Advantage</th><th>Disadvantage</th></tr>
<tr><td rowspan="2">Model-based prediction</td><td colspan="2">Electrochemical model</td><td>The internal and external characteristics of the battery to consider the actual aging mechanism of the battery and simulate the aging process of the battery</td><td>Complete theory and high precision</td><td>Complex mathematical equation; difficult to solve external environmental factors</td></tr>
<tr><td colspan="2">Equivalent circuit model</td><td>Circuit components to simulate the dynamic characteristics of the battery</td><td>Simple structure and easy for data analysis</td><td>Slightly lower than the electrochemical model</td></tr>
<tr><td rowspan="7">Data-driven prediction</td><td rowspan="4">Stochastic Filtering Algorithm</td><td>Particle filter (PF)</td><td rowspan="7">Can be used to analyze degradation characteristics and predict remaining life</td><td rowspan="7">Not required to have a lot of relevant professional knowledge</td><td rowspan="7">Less accurate than model-based methods</td></tr>
<tr><td>Unscented particle filter (UPF)</td></tr>
<tr><td>Extended Kalman filter (EKF)</td></tr>
<tr><td>Unscented Kalman filter (UKF)</td></tr>
<tr><td colspan="2">Time series analysis method</td></tr>
<tr><td colspan="2">Regression analysis method</td></tr>
<tr><td colspan="2">Machine Learning</td></tr>
</table>

The machine-learning method needs a large number of historical data to train the model, which is suitable for the large amount and high quality of data, mainly including the artificial neural network (ANN), support vector machine (SVM), and relevant vector machine (RVM). Parthiban et al. [101] presented an artificial neural network to understand the charge–discharge characteristics of the lithium-ion battery and found that there was excellent consistency between the calculation capacity and the observation capacity. Wu et al. [102] proposed an evaluation method for the online estimation of RUL of lithium-ion battery, using FFNN and IS, and they verified it by conducting an experiment and numerical simulation. Pattipati et al. [103] proposed an SVM model to predict the SOC, capacity attenuation, and power attenuation. The estimated values of capacity attenuation and power attenuation are used to estimate the remaining useful life (RUL) of the battery by SVM regression. Liu et al. [104] implemented a flexible and effective online training strategy in the RVM algorithm to enhance the prediction ability based on the incremental optimization RVM algorithm through efficient online training. They presented a simple and effective online training strategy of the RVM algorithm to achieve high prediction performance. The model-based method is widely used, and the data-driven method requires the completeness of historical data, making it vulnerable to the uncertainty of the data. However, the hybrid prediction method has gradually become a potential trend in the field of residual life prediction of the lithium battery, and it usually needs to integrate the prediction modeling methods and data-driven methods. Chang et al. [105] presented a hybrid method based on fusion technology to effectively improve the prediction accuracy, including poor model generalization, unstable prediction, complex parameters, and a large number of calculations.

## 4. Disassembly Planning and Operations Management

The disassembly of the retired EV batteries is an extremely critical step in echelon utilization and the EV battery recycling process. The retired products or parts must be completely disassembled before their further disposal. The disassembly of EV batteries can be defined as a remanufacturing process, which is to decompose all the EV battery modules and/or cells into the useful components of the EV batteries. Battery disassembly is easily restricted by economic, environmental, and current uncertain disassembly processes; this is recognized as one critical research point and bottleneck technology issues in the next research study [106]. However, disassembly safety problems in the disassembly process of the EV battery are facing many huge challenges. Obvious disassembly differences exist between decommissioned batteries due to various battery classes and quality difference, resulting in different disassembly methods for EV battery modules and cells. Owing to the fact that retired EV batteries are composed of hazardous chemical ingredients [107], the disassembled EV battery generally contains residual electricity, which can easily cause an unnecessary accident or even an explosion. The battery cells are connected by welding. If the battery disassembly is not accurate to position in disassembly operations, the disassembly tool might penetrate the battery to cause the electrolyte overflow and explosion [30].

### *4.1. Disassembly Optimization Methods*

The complete disassembly is often considered to acquire the optimal economic benefit and environmental friends, while partial disassembly has more advantages to support the echelon utilization for the EV battery [108]. There are many problems for the EV battery disassembly process, e.g., the optimal disassembly process or disassembly depth for the retired EV battery. Traditional remanufacture seeks the best disassembly level of the product. It improves product performance by replacing certain parts to balance economic benefits and disassembly depth [109]. However, this cannot maximize the use of retired batteries, so we need to determine the depth of battery disassembly by combining the parameters of the battery characteristics and economic and environmental requirements. Owing to the complexity of connection types from disassembled EV batteries (e.g., mechanical fasteners, such as nuts and bolts, spring clasp, screws, snaps, crimping, etc.; welding and welded joints through various welding processes; and bonded joints for electrical insulation, sealing, and thermal conductors, etc.), it is necessary to determine the optimal disassembly sequences and operations under the safety status. However, it is preferable to adopt the non-destructive disassembly methods to accomplish the disassembly tasks (i.e., screwing and selective soldering). From the battery pack to the modules, then to the cells, making decisions for the disassembly sequence is required to determine the optimal disassembly depth and how to remove the lid, the electrical/mechanical/chemical connection, the electronic component, the module, the battery, and even the cathode, anode, separator, and electrolyte in the battery disassembly process [110]. Therefore, it is important to make reasonable disassembly planning for the specific disassembly tasks to realize the disassembly sequence optimization, as shown in Table 8.

**Table 8.** Related works from the literature about optimization methods for disassembly process.

| Ref. | Optimization Methods | Advantage | Disadvantage |
| --- | --- | --- | --- |
| Go et al. [111] | GA | Provides an optimum disassembly sequence in a short execution time. | It is dependent on the disassembly time |
| Zhang et al. [112] | GA–GM | Considers a parallel disassembly path-planning problem with fuzzy time, focusing on minimum overall operation time and cost. | Not suitable for large products |

**Table 8.** *Cont.*

| Ref. | Optimization Methods | Advantage | Disadvantage |
| --- | --- | --- | --- |
| Agrawal et al. [113] | GA–PPX | Provides an integrated solution from CAD assembly model to disassembly sequence, planning and simulation. | Does not apply to most of the parts |
| Pornsing et al. [114] | DPSO | Proposed a dynamic precedence matrix for coping with the precedence constraints of the problem. | DPSO parameters still need to be tested |
| Shan et al. [115] | ACO | Not only the sequence of parts in product was optimized, but also other information in the disassembly process was also optimized. | Stability needs to be solved |
| Mukul et al. [116] | ASGA | Better results than ACO algorithm or GA. | Higher computation time compared with GA |
| Guo et al. [117] | SS–PR | To optimize and the selective disassembly sequence with multi-constraints to maximize disassembly profit. | Not applicable to all product types |
| Adenso-Diaz et al. [118] | GRASP | To solve these problems with composite structures and constraints. | It takes a long time |

GA, Genetic Algorithm; DPSO, discrete particle swarm optimization; ACO, Ant Colony; ASGA, algorithm of self-guided ants; SS, scatter search; GRASP, greed randomized adaptive search procedure.

In order to deal with the uncertainty disassembly of the retired EV batteries, as shown in Figure 2, many works from the literature were reviewed to explain a potential trend for disassembly optimization. Tian et al. [119] proposed a fuzzy variable representation of the uncertainty disassembly of batteries to maximize disassembly profit based on AND/OR graph, which combined fuzzy simulation and artificial bee colony to solve the disassembly sequence planning. Feng et al. [119] proposed a disassembly sequence planning model to deal with disassembly complexity and disassembly cost, using an improved multi-objective optimization algorithm, which is used to deal with the uncertainty and complexity based on fuzzy theory in the disassembly process by considering the potential impacts on environmental during the disassembly process. Feng et al. [120] considered the maximum recovery profit and the minimum impact on environment to optimize the hybrid disassembly planning tasks, which are demonstrated by the disassembly process based on CNC machine tools. Alfaro-Algaba et al. [53] presented a case of the battery disassembly from the Audi A3 as an example to maximize economic benefits with the minimum environmental impacts, which can be used to design the remanufacturing disassembly process of the EV battery packs. Similarly, Wegener et al. [110] discussed an approach of disassembly sequence planning using the battery system of the Audi Q5 Hybrid and VM Jetta as an example. The structure of Audi Q5 hybrid battery system can be disassembly based on the disassembly priority graph combined with the disassembly sequence optimization. They apply the part-priority matrix to disassembly sequence to improve the efficiency of disassembly. Marshall et al. also developed the disassembly sequence planning of EV batteries to further refine the recycling ways. In addition, most disassembly optimization methods only focus on a static process, which cannot dynamically adapt to the uncertainty in the disassembly process. Ke et al. [121] used mixed graphs and matrices to represent the relationship between battery parts and priority disassembly levels, providing a method for the target optimal disassembly sequence and the shortest disassembly path. Xiao et al. [122] proposed an uncertain disassembly sequence optimization method based on the dynamic Bayesian network in the disassembly process, which developed a feasible disassembly graph model to describe the relationship between disassembly objects. However, it is necessary to discuss the complexity of disassembly based on the design of disassembly operations and tasks by considering partial automation (e.g., collaboration robot, etc.) in the specific disassembly process.

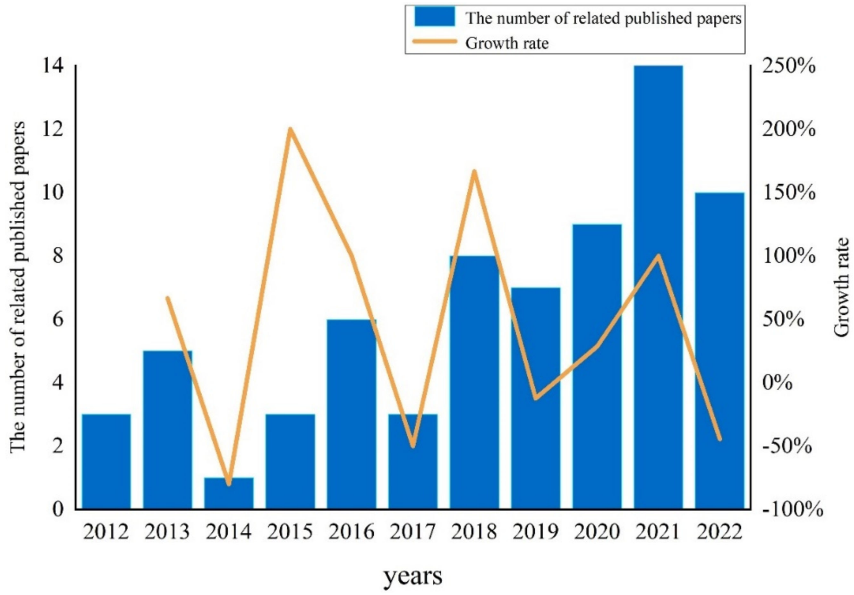


**Figure 2.** Statistics of published papers of disassembly sequence optimization.

In the face of large-scale and aged inconsistent degrees of retired EV batteries, static methods cannot be used on various batteries. If each disassembly is to be used to generate the sequence of methods manually set up and adjust them, then it is undoubtedly a huge workload. The sequence optimization approach based on dynamic Bayesian networks was mentioned above, which gives us an idea: using machine learning to make the computer get a general model to adapt to different characteristics of the battery. This idea is also practiced in echelon utilization [123]. They are widely used to assess the battery state. Paul et al. [124] proposed the machine-learning-based prediction of battery capacity from impedance. Hector et al. [125] used charge/discharge curves to predict battery aging in large amounts of data. With the improvement of battery historical data and iterative update of algorithm, we will see increased application of machine learning in battery disassembly sequence.

*4.2. Robot-Assisted Disassembly Operations*

The disassembly process of the battery pack will produce harmful substances, including the disassembled battery cells. However, it might cause electrolyte leakage problems in the disassembly operations of the EV battery cells if the manual disassembly makes it difficult to avoid the human safety problems. In addition, the disassembly process of the battery pack and module is time-consuming when it comes to reaching the efficiency of the production requirements. Furthermore, there are many uncertainties in the battery pack that make it difficult to completely accomplish the automatic robot disassembly at the current production level with uncertain and complex disassembly products. Therefore, the design of semi-automatic/automatic disassembly production lines can be used to improve the efficiency of uncertain disassembly to assist the human-centered disassembly task as a research hotspot. Currently, fully automated disassembly does not offer more advantages in both technical and economic terms for high-quality battery disassembly tasks. Therefore, it is necessary to focus on the disassembly of human–robot collaboration [106]. The concept of battery disassembly workstation was proposed to complete some simple and mechanical disassembly tasks based on a platform of robot-assisted working disassembly [126]. Schäfer et al. [127] proposed a remanufacturing station to automatically assign disassembly takes to finish the product removals.

The disassembly of the battery has many safety issues based on experienced operators or robots, which is a high risk of disassembly operation, especially in many special disassembly environments (e.g., disassembly in a heating system, freezing airs, or even solvent). The remote manipulation of disassembly can solve the problem of human security to the greatest extent, which can be widely used in dangerous or uncertain environments [128]. Remote manipulation of disassembly has three basic operation modes. The first direct control and manipulation of the robot can be used to complete the disassembly tasks. This operation mode can complete the disassembly target by remote human operations [129]. However, due to the multilevel structure of the battery pack, the battery disassembly needs the robot-assisted flexibility disassembly of human operations [130]. The second disassembly operation mode is to implement remote supervision and the robot motion feedback, which will be detected and estimated in real time through the network system. Humans can interact with the information for the robot motions in a safe area by guiding the robot execution paths. The third operation mode is controlled by a human and robot together, which still relies on deep intelligent algorithms to make robots determine the disassembly process by imitating and learning human disassembly actions. Due to the complexity of the EV battery recycling, the productivity and flexibility of robot-assisted disassembly needs to be improved for the uncertain product structure and quality to complete the disassembly task directly with human–robot collaboration in a working station. As mentioned above, the disassembly process of human–robot collaboration is very different from the traditional robot manufacturing that makes the robot in the same working station with the human to accomplish the specific disassembly tasks, as shown in Figure 3. Many researchers have explored the research points to accomplish higher efficiency and intelligent decision-making in the disassembly process. This makes robots have more intelligent decisions.

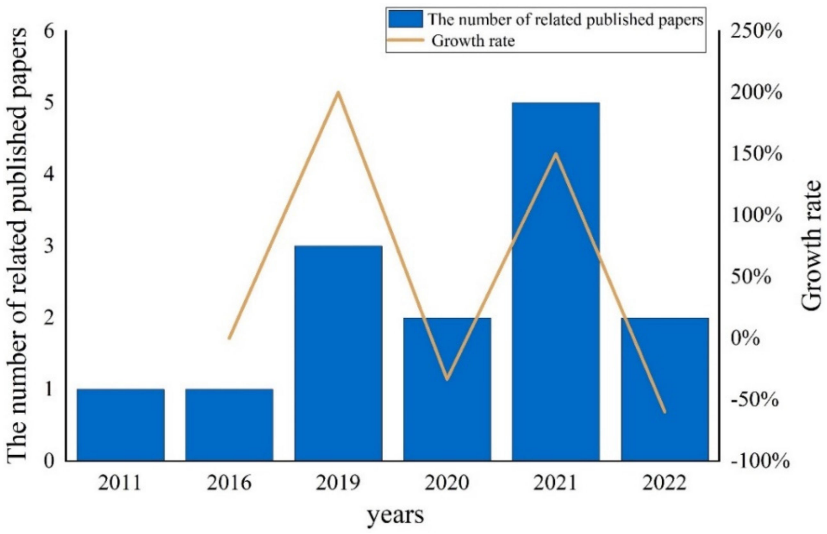


**Figure 3.** Statistics of published paper on human–robot-collaboration disassembly.

*4.3. Disassembly Task Safety*

The safety issues for EV battery disassembly and recycling are huge challenges for traditional robot manufacturing. It is necessary to install a guardrail in the working area of the robot to prevent the robot from causing collision accidents. However, the human and the robot share the working space in the disassembly working mode, thus making it impossible to install a guardrail to protect the safety of the human. Therefore, many scholars have studied the safety protection of human–robot collaboration by focusing on security disassembly. In order to ensure personal safety in the human–robot-collaboration disassembly process, a collision-detection method should be proposed to solve these problems, including safety detection, human and robot identification, and classification and optimization reaction [131,132]. The detection method can effectively reduce the contact force to a level that is not dangerous to humans. The collision force of ordinary robots will increase rapidly after a collision. The application of collision detection can effectively prevent the robot from causing a secondary crushing injury to humans after a collision.

As shown in Figure 4, many scholars have studied the force/torque sensor installed on the robot arm to detect the collision of the manipulator [133], including the adaptive control law [134] or Kalman filter [135] to analyze the collision possibility of disassembly operations. However, these methods can only detect the robot motion collision on the end effector. If the collision is caused by another motion robot, it cannot be accurately detected unless force sensors are installed in all parts of the robot. Many researchers have proposed collision-detection methods based on the comparison between the actual motor torque and the calculated torque according to the mechanical force model [136,137]. However, these methods need to install torque sensors at the joints of the disassembly robot, and they cannot obtain accurate models to explain the nonlinear joint viscous friction. Some researchers focused on dynamic modeling of robots to perform collision detection without external sensors [138]. The initial method can be used to compare the command input torque with the actual input torque [139,140]. In order to achieve the performance of accurate safety detection, a real-time collision-detection method can be proposed to consider more effective methods than using external sensors that can reduce the accuracy of monitoring signals for model uncertainty and interference [141]. Heo et al. [142] designed a deep neural network model to predict the disassembly robot collision, which can improve the performance of disassembly collision detection. After the collision of the robot is detected, it is necessary to control the robot motion and disassembly operations in the disassembly process [136,143]. However, stopping the robot motions does not necessarily guarantee human safety. If the robot can return to the original path after collision, it will be more convenient to continue working after the operator returns to the safe range. It does not need to restart the robot every time.

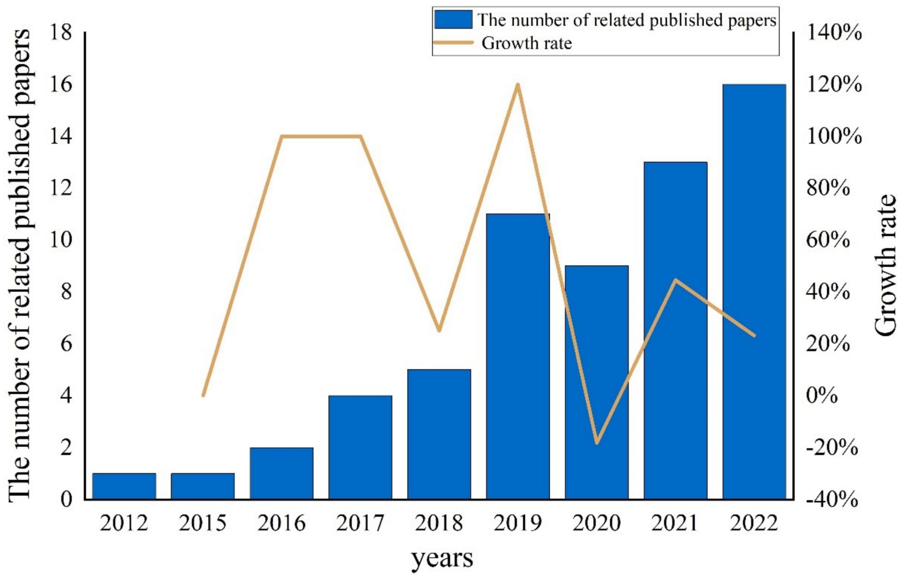


**Figure 4.** Statistics of published papers on collision-detection applications.

Related detection methods were reviewed by many works from the literature that demonstrated their various advantages and disadvantages for avoiding robot collisions. In the human–robot collaboration operation environment, if the robot can recognize human actions to make predictions and plan a reasonable motion path to prevent collisions according to human actions, it can improve the efficiency and safety of disassembly process. Therefore, some researchers began to study human intention recognition. It is generally realized through machining vision recognition and force recognition. Humans understand the environmental information by perception and experience reasoning through their thoughts and eyes. Therefore, machining vision recognition is often used in the research of object positioning. Wang et al. [144,145] proposed a robot-assisted manufacturing framework of working environment perception to detect the workers' actions based on machining vision recognition, which can be used to establish accurate and reliable context awareness. The deep learning method is used as a data-driven technology to continuously analyze human intentions to reasonably plan the robot's motion path. Liu et al. [146] proposed a human–robot collaboration system of UAV based on environment awareness, which considered three depth vision cameras (Kinect) to collect point cloud data, and they built a virtual space through the Octagon algorithm [147]. The three-dimensional images of the human body and the position of the robot are imported into the virtual space, which are combined to detect the human operation intention in real time to improve the assembly efficiency to ensure the safety of the human body. Other scholars proposed a deep learning method to analyze human intentions by recognizing the posture of their hands. Oyebade et al. [148] improved the efficiency of a complex disassembly task through a convolutional neural network and stack de-noising self-encoder, but it cannot handle the clutter interference problem in gesture recognition as shown in Table 9.

**Table 9.** Related detection methods and their application advantages and disadvantages.

| Ref. | Methods | Advantage | Disadvantage |
| --- | --- | --- | --- |
| Alessandro et al. [139] | FDI (Fault detection t and isolation) | When contact is detected, you can switch to the hybrid force/motion controller to adjust the interaction force. | For faster collisions with harder environments; the method for analyzing the transient phase after the first collision still needs to be improved. |
| Dirk et al. [149] | Image recognition | No sensor is required. | A discretization error occurred during the synthesis of differential images. Some configurations were actually occupied, but the collision test was reported as idle. |
| Heo et al. [142] | Deep learning | Improve detection performance. | Vulnerable to model uncertainty and noise signals. |
| Lu et al. [150] | Force sensor | No need to modify the existing design of industrial robots. | The collision at the end of the robot can only be identified. |
| Makris et al. [151] | Visual recognition | It can not only detect the collision between robot structure and human, but also consider the robot tools. | The distance between robot and human may not be recognized correctly. |
| Rodrigues et al. [152] | Deep learning | It can provide rapid decision-making for events in collaborative scenes and reduce possible harm to humans and interactive robots. | The accuracy of collision detection is not 100%. |
| Huang et al. [153] | Back-input compensation | It can effectively detect soft (slow) collision and hard (fast) collision. | Only rigid joints. |
| Lu et al. [154] | Camshift Algorithm | High stability, fast speed, and accurate calculated collision point position. | There are high requirements for the placement of binocular cameras. |
| Maric et al. [155] | Visual recognition | Minimize interference in robot trajectory. | It depends on the speed of the end effector. If the speed is fast, the scanning volume is large and takes a long time. |

As shown in Figure 5, there are many works in the literature that involve machining vision recognition for robot-assisted disassembly manufacturing. As is known, the machining vision system cannot play a significant role in intention recognition, so intelligent sensors are needed to assist the specific disassembly operations. For example, direct human–robot collaboration technology can be accomplished by using force torque sensors on the end actuator or other joints of human–robot collaborative disassembly, or by integrating tactile robot skin technology [156]. Many scholars transferred the detection target of the mechanical sensor to the human body. Boris et al. [157] applied pressure sensors capable of recognizing various human sitting, standing, and lying positions into pressure arrays and embedded them in cushions, carpets, and mattresses to judge worker motions. In further research, Kinugawa et al. [158] established a prediction model for worker movement trajectory by detecting forces with intelligent sensors.

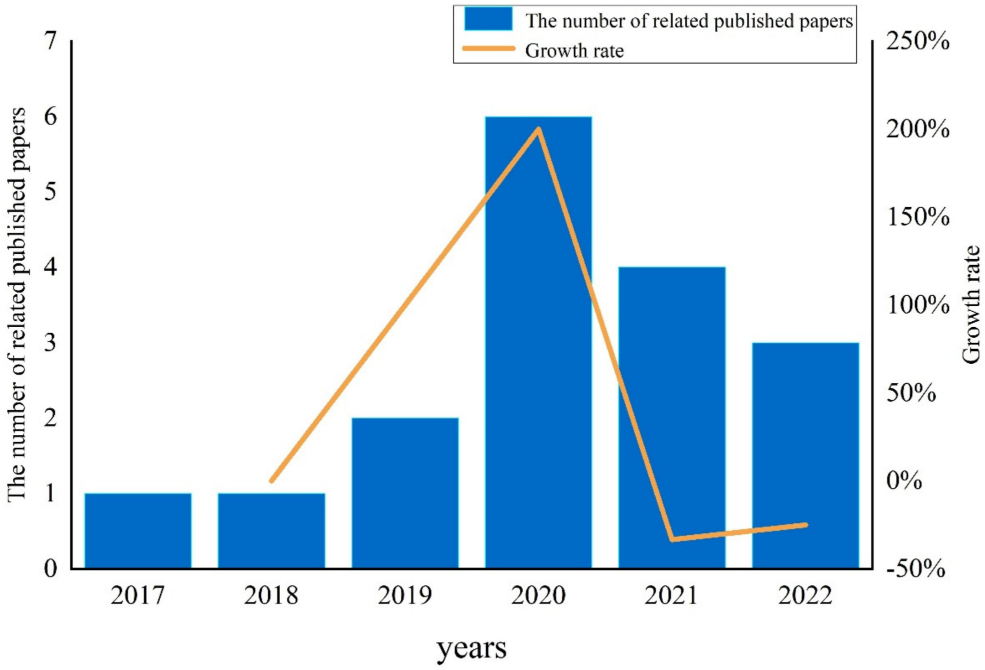


**Figure 5.** Statistics of published papers on machining vision-recognition methods for robots.

## 5. Discussion

With the extensive requirements of electric vehicle (EV) battery recycling, the echelon utilization and disassembly technology of retired EV batteries have become a potential trend to efficiently improve the recycling of retired EV batteries in sustainable development. Therefore, there are many research points that can be further discussed:

- First of all, in order to ensure the safety of product echelon utilization and make full use of recycled electric vehicle batteries, it is necessary to efficiently recycle the retired EV batteries. We discussed the evaluation methods based on three significant indicators (SOH, SOC, and RUL) that affect the battery performance in various application scenarios. We cannot directly and accurately measure the corresponding index parameters, but we can estimate or predict them by using related algorithms. Therefore, it is necessary to improve the accuracy of battery performance prediction so that the related parameters and complex calculation can be acquired to improve the efficiency of automatic disassembly manufacturing as a new research point.
- Secondly, the disassembly of EV batteries is carried out manually. However, as a large number of EV batteries need to be disassembled and recycled, manual disassembly cannot complete such a large amount of work in a specified time, so improving the efficiency of disassembly will bring a lot of benefits. Therefore, we will improve the efficiency of disassembly by optimizing the disassembly sequence and disassembly operation by automatic robot-assisted disassembly technology.
- Many scholars have studied the optimization of disassembly sequence, but most of the disassembly modeling cannot dynamically adapt to the uncertainties in the disassembly process; however, there are a lot of uncertainties in battery disassembly. In addition, many scholars often do not consider the impact of environmental factors and disassembly constraints in their research. For disassembly sequence optimization, parallel disassembly and dynamic disassembly sequence optimization will still be a future research point with the gradual application of human–robot collaboration in industrial disassembly production lines; the optimization of disassembly operation should consider the execution of both human and robot.

In order to improve the efficiency of battery disassembly and echelon utilization, it is necessary to select the human–robot collaboration technology for the disassembly tasks and operations. Accordingly, it is necessary to discuss the security problems based on human–

robot collaboration disassembly in further higher efficient disassembly and recycling for retired EV batteries, including human-intention recognition and collision detection:

- At present, most human–robot collaborative safety protection can be completed by collision detection. However, the accuracy of collision-signal recognition and screening still needs to be improved. Most scholars designed it so that the robot stops working after collision. However, simply stopping does not necessarily guarantee human safety. If the robot can return to its original path or move far away from people after a collision, it will not only greatly improve the safety but also save the time to restart the robot. Therefore, more efficient robot-assisted disassembly detection is a huge difficultly to deal with in relation to the complex coupling relationships between human and robot interactions.
- The research of human intention recognition is still in its infancy. Most scholars predict human actions by recognizing the human hand posture to reasonably plan the trajectory of the robot to complete collision avoidance. In addition, the accuracy of human-intention recognition still needs to be improved. Many scholars also installed sensors on human operators to complete motion prediction. In the future, it will be possible to detect visual force recognition for human-intention recognition to improve the accuracy of prediction.

## 6. Conclusions

This paper reviewed the recycling status of electric vehicle (EV) batteries and pointed out that retried EV batteries are not recycled by disassembly technology and echelon utilization. We analyzed the challenges of echelon utilization:

- The uncertainty of the use environment and scene mode of the battery makes it difficult to accurately judge the level and scene of the battery echelon utilization by the specific parameters of the battery.
- The decay rate of retired batteries will increase in the process of echelon utilization, which will affect the continuity of battery utilization and make it difficult to guarantee the economic benefits of echelon utilization.
- For retired batteries, considering safety and economic considerations prior to echelon utilization, the parameters and performance of the batteries need to be evaluated to support optimal application scenarios.

Therefore, we analyzed the three health indicators of echelon utilization, namely SOH, SOC, and RUL. Their existing evaluation methods were introduced and analyzed in detail. Then we presented the challenges of battery disassembly:

- The inconsistency of the battery is the biggest challenge; we need address it according to different parameters and different physical structures to develop a different disassembly strategy.
- Based on the above point, the huge disassembly demand leads to a great increase in the workload of disassembly. We need to improve the efficiency of disassembly on the basis of optimizing the disassembly sequence.
- There are many safety issues in the disassembly process. There is an urgent need for appropriate tools (robots) and reasonable planning of disassembly strategies.

We analyzed the problem in terms of disassembly optimization and human–machine collaboration and tried to summarize previous work. We pointed out that the safety problems of human–robot collaboration need to focus on collision detection and human-intention recognition by reviewing many related works from the literature. Finally, we comprehensively discussed the current issues related to echelon utilization and disassembly in retired-EV-battery recycling and gave relevant suggestions. The echelon utilization and dismantling of batteries is the combination of economic benefit and a safety problem. We focused on achieving this in a safer, more profitable way.

**Author Contributions:** Conceptualization, J.X. and B.W.; methodology, J.X.; software, J.X.; validation, J.X., B.W. and C.J.; formal analysis, J.X.; investigation, C.J.; resources, J.X.; data curation, B.W.; writing—original draft preparation, J.X. and C.J.; writing—review and editing, J.X.; visualization, B.W.; supervision, J.X.; project administration, J.X.; funding acquisition, J.X. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

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