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Review

Echelon Utilization of Retired Power Lithium-Ion Batteries: Challenges and Prospects

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Abstract: The explosion of electric vehicles (EVs) has triggered massive growth in power lithium-ion batteries (LIBs). The primary issue that follows is how to dispose of such large-scale retired LIBs. The echelon utilization of retired LIBs is gradually occupying a research hotspot. Solving the issue of echelon utilization of large-scale retired power LIBs brings not only huge economic but also produces rich environmental benefits. This study systematically examines the current challenges of the cascade utilization of retired power LIBs and prospectively points out broad prospects. Firstly, the treatments of retired power LIBs are introduced, and the performance evaluation methods and sorting and regrouping methods of retired power LIBs are comprehensively reviewed for echelon utilization. Then, the problems faced by the scenario planning and economic research of the echelon utilization of retired power LIBs are analyzed, and value propositions are put forward. Secondly, this study summarizes the technical challenges faced by echelon utilization in terms of security, performance evaluation methods, supply and demand chain construction, regulations, and certifications. Finally, the future research prospects of echelon utilization are discussed. In the foreseeable future, technologies such as standardization, cloud technology, and blockchain are urgently needed to maximize the industrialization of the echelon utilization of retired power LIBs.

Keywords: electric vehicles; retired power lithium-ion battery; echelon utilization; sorting and regrouping

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1. Introduction

Resources consumption is a prerequisite for supporting the industrialization process. The shortage of resources has become a serious problem humans face in recent years [1]. The United Nations proposes the 2030 Sustainable Development Goals, which aim to call on the world to act together to protect the planet and improve the lives and futures of all people [2]. The United States has also formulated a green development strategy to realize 100% clean energy generation by 2035. The Chinese government has also pledged to the world to achieve carbon peaking by 2030 and carbon neutrality by 2060 [3]. Cars are the most used means of transportation in people's daily travel, but traditional fuel vehicles are no longer in line with the theme of green and sustainable development. Under such a background, electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) have been favored by governments and people all over the world because of their advantages of low pollution, low noise, and high economy [4]. According to the data released by the International Energy Agency, from 2010 to 2021, global sales of EVs and PHEVs are increasing yearly, as shown in Figure 1a. In 2021, EV sales will account for more than 9% of global vehicle sales. In Europe and China, the proportion of EV sales has exceeded 15%, as shown in Figure 1b,c, respectively. As shown in Figure 1d, EV sales share exceeds 4% even in the US, where EV sales are low [5].

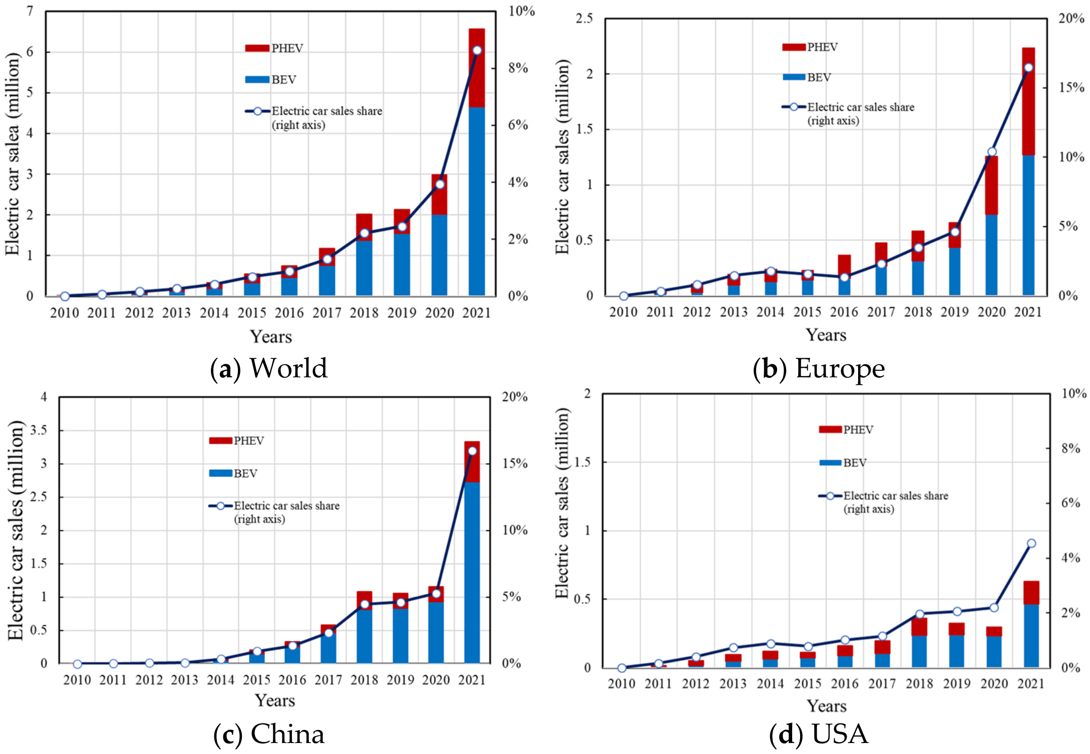

Figure 1. EV and PHEV sales and EV sales share. (**a**) World (**b**) Europe (**c**) China (**d**) USA.

The increasing number of EVs and PHEVs has led to the rapid development of the battery industry. As shown in Figure 2a, the demand for electricity from BEVs and PHEVs is increasing yearly. The batteries currently used in EVs include nickel-hydrogen batteries, lithium iron phosphate batteries, and lithium-ion batteries (LIBs). LIBs have become the most used power source for EVs due to their green environmental protection, long service life, large capacity, and high charge and discharge safety [6,7]. A practical problem that cannot be ignored is that the capacity of LIBs will degrade with the increase in charging and discharging times. When the capacity of the LIB degrades to about 80% of the rated capacity, the LIB will face retirement. Disposal of LIBs decommissioned on such a large scale is quite troublesome. With the gradual increase of EVs and PHEVs, the echelon utilization of retired LIBs is gradually occupying a research hotspot. Figure 2b shows the global LIBs recycling scale and growth rate. By 2025, the global retired power LIBs will be estimated to exceed 600,000 tons.

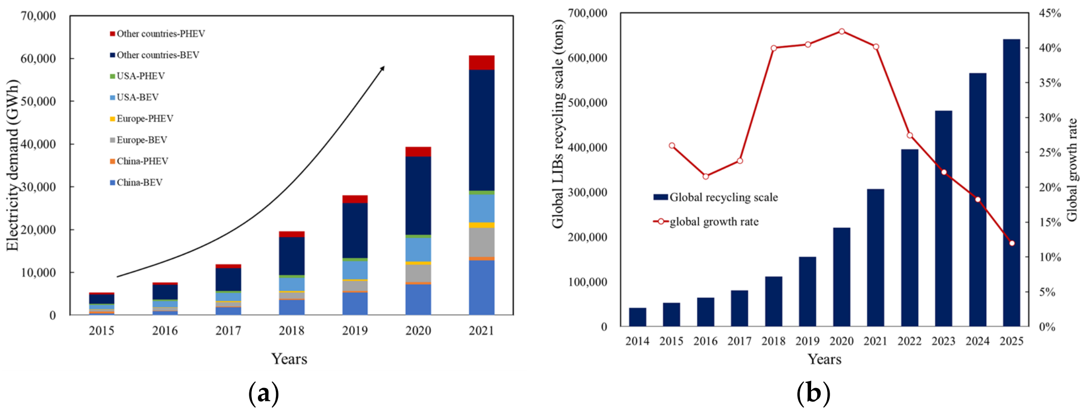

Figure 2. BEV and PHEV electricity demand (**a**) and global retired LIBs recycling scale (**b**) [5,8].

In the face of such many retired LIBs, if they are directly discarded, they pollute the environment and cause a huge waste of resources, which is not in line with the 4R principle (recycle, reuse, reduce, and recover) [9,10]. Many scholars choose to recycle many valuable materials in retired LIBs, such as anode and cathode materials, by using physical or chemical means [11,12]. However, echelon utilization is a better choice for most retired power LIBs and is also the main direction of future research development [13]. Echelon utilization can fully use the remaining energy in retired power LIBs, such as grid energy storage and 5G base stations [14]. However, some problems exist in the large-scale echelon utilization of retired power LIBs. Performance screening indicators, clustering methods, economic evaluation, supply chain construction, safety management, etc., are all major challenges for the echelon utilization of large-scale retired power LIBs [15,16].

In this study, we introduce several treatment methods for the current large number of retired power LIBs in Section 2. Echelon utilization is regarded as one of the most promising solutions to deal with retired power LIBs. In Section 3, we review the research status of the echelon utilization of retired power LIBs, including the performance evaluation indicators of retired power LIBs and the technical challenges of sorting and regrouping. Section 4 discusses the scenarios and economics of echelon utilization, which is also one of the most concerning issues for investors. The problems and technical challenges faced in the echelon utilization of retired power LIBs are reviewed in Section 5, including safety performance evaluation, economics, industry chain, policies, and guidelines. Section 6 mainly looks forward to future research, provides references, and points out the direction for future research work. Section 7 summarizes the review and gives the conclusions.

2. Treatment of Retired Power LIBs

2.1. Battery Materials Recycling

In the process of commercializing LIBs, the acquisition of raw materials is expensive. Figure 3 shows a schematic diagram of a cylindrical LIB's shape, composition, and charging and discharging process. It can be seen from Figure 3 that when the LIB is charged, the cathode electrode releases lithium ions, and the lithium ions pass through the separator through the electrolyte and move to the anode electrode. When the LIB is discharging, the movement of lithium ions is just the opposite. Lithium ions enter the electrolyte from the anode electrode, pass through the separator, and finally reach the cathode electrode.Typical cans for retired power LIBs are usually iron or aluminum; a mixture of graphite, conductor, binder, and the electrolyte is coated on the copper foil as the anode material of the retired LIBs [17]. The cathodes of retired power LIBs are generally aluminum foils coated with cathode materials, conductors, polyvinylidene fluoride binders, and fluoride salts. The separator material between the cathode and anode also prevents short circuits between the positive and negative electrodes [18]. From a sustainability perspective, recycling retired LIBs can reduce resource consumption; from an economic perspective, recycling retired LIBs can reduce the cost of raw material supply; from a political perspective, recycling retired batteries can reduce dependence on foreign resources, which has long-term strategic significance [19].

Table 1 shows the mass proportion of typical metals in several common LIBs, and we also list the metal transaction prices obtained from the London Metal Exchange (LME) in Table 1. It can be seen from Table 1 that the metal materials in retired power LIBs are expensive (such as cobalt is about three times as expensive as nickel) and have high recycling value and prospects. In the existing research, recovering lithium, nickel, cobalt, and copper metal materials is the main research direction for recycling retired power LIB materials [20]. In fact, the recycling of other low-priced materials and the recycling of electrolytes is also an unavoidable problem [21]. However, electrolyte recovery has problems such as a complex recovery process, high cost, high energy consumption, and serious volatilization of toxic and harmful gases. These problems are also the challenges that need to be solved in the industrialization process of electrolyte recovery.

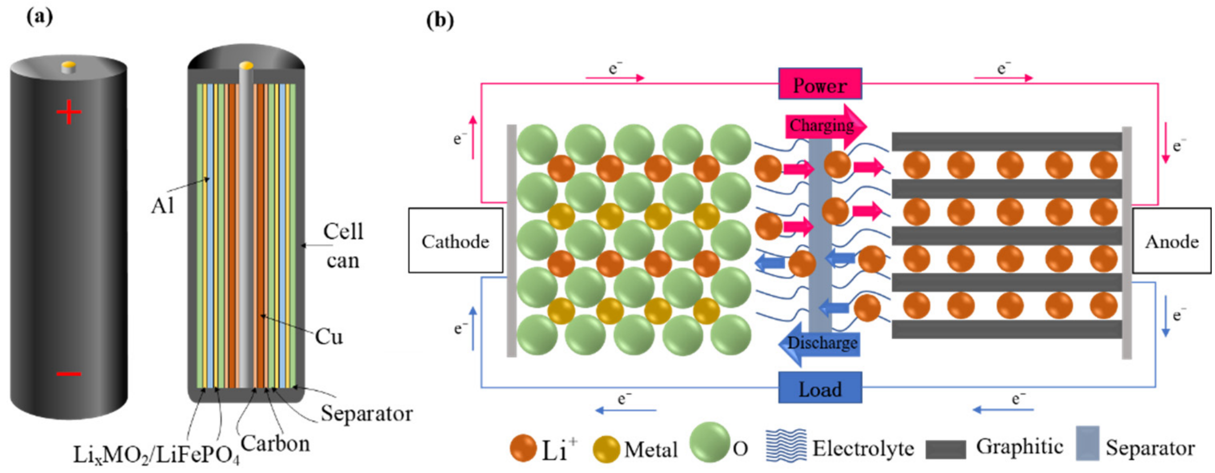

Figure 3. A schematic diagram of a cylindrical LIB's shape, composition, and charging and discharging process (**a**) Shape and composition of cylindrical LIB. (**b**) Schematic diagram of the charging and discharging process of LIB.

Table 1. Mass compositions of typical LIBs.

Metals	**Cathode Material**					**Prices ($/kg)**
	$LiCoO_2$ (Mass%) [22]	**$LiFePO_4$(LFP) (Mass%) [23]**	**$LiMn_2O_4$ (Mass%) [23]**	**$LiNi_{1/3}Mn_{1/3}Co_{1/3}O_2$ (NMC) (Mass%) [24]**	**$LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ (NCA) (Mass%) [25]**	
Aluminum	5.2	6.5	21.7	22.72	21.9	2.36
Cobalt	17.3	0.0	0.0	8.45	2.3	49.81
Copper	7.3	8.2	13.5	16.60	13.3	9.456
Iron/steel	16.5	43.2	0.1	8.79	0.1	0.73
Lithium	2.0	1.2	1.4	1.28	1.9	11.75
Manganese	0.0	0.0	10.7	5.86	0.0	2.30
Nickel	1.2	0.0	0.0	14.84	12.1	16.16
Binder	2.4	0.9	3.7	1.39	3.8	N/A
Electrolyte	14.0	14.9	11.8	11.66	11.7	N/A
Plastic	4.8	4.4	4.5	3.29	4.2	N/A

The advantages and disadvantages of the main recycling methods for retired power LIB materials are shown in Table 2. The recycling methods mainly include pyrometallurgical, hydrometallurgical, bioleaching, and direct recycling [26,27]. Pyrometallurgy reduces metal oxides to cobalt, copper, iron, and nickel alloys at high temperatures. Hydrometallurgy mainly leaches the desired metals from the cathode material using special solution reagents [28]. The bioleaching method refers to the use of bacteria to recover valuable metals. Still, the difficulty of this method is that the bacteria are cultured for a long time and are easily contaminated. Nonetheless, the method has also been used in industries such as mining. The process of removing the anode and cathode materials of retired power LIBs and then repairing, processing, and manufacturing them for reuse is called direct recycling.

Table 3 lists the current worldwide retried power LIB materials recycling companies and their recycling technologies. It can be seen from Table 3 that the most widely used recycling methods in industry are pyrometallurgy, hydrometallurgy, and pro-and hydrometallurgy. Figure 4 is a process flow diagram of three recycling methods developed by different companies. The pyrometallurgy method developed by the German company Accurec is mainly used to recycle Co alloy and Li metal. The hydrometallurgy method developed by the French company Recupyl is mainly used to recover $Co(OH)_2$, Li_2CO_3, and Li_3PO_4. The pro-and hydrometallurgy method developed by the Umicore company in the US is mainly used to recover $CoCl_2$ and $Ni(OH)_2$.

Table 2. Comparison of several methods for recycling retired power LIB materials.

Study	Recycle Method	Advantages	Disadvantages
Refs [29,30]	Pyrometallurgical	Relatively mature technology, simple process	Low recovery rate, high cost, large environmental pollution
Refs [15,31]	Hydrometallurgical	High recovery rate, high efficiency, low power consumption	Relatively complex process, high resource consumption, low efficiency, long production time
Refs [32,33]	Bioleaching	Low cost, low environmental pollution, low energy consumption	Relatively complex process, long time cultivation
Refs [34,35]	Direct recycling	Simple process, low cost, low environmental pollution	Immature technology, difficult to commercialize

Table 3. Comparison of industrial recycling of retired power battery materials [1,36–38].

Related Company	Battery Type	Recycle Method	Recovered Product	Country
Accurec-recycling Gmbh	Except Pb and Hg	Pyrometallurgy	Co, Li	Germany
AEA	All	Hydrometallurgy	Co_2O_3, LiOH	UK
AkkuSer Oy	All	Pro-and hydrometallurgy	Meal powder	Finland
Batrec industrie AG	Li-based, Hg-based	Pyrometallurgy	Co, MnO_2, Ni	Switzerland
Brunp recycling	Li-based, Ni-based	Hydrometallurgy	Cathode	China
GEM	Li-based, Ni-based	Hydrometallurgy	Cathode	China
Glencore Plc	Li-based	Pro-and hydrometallurgy	Co, Ni, Cu	Switzerland
IME	Li-based, Ni-based	Pro-and hydrometallurgy	Li_2CO_3, Co	Germany
International Metals Reclamation Company	Li-based, Ni-based	Pyrometallurgy	Ni alloys	US
JX Nippon Mining & Metals	Li-based	Hydrometallurgy	Ni, Co, Mn, Li	Japan
Mitsubishi	Li-based, Pb-acid	Pyrometallurgy	$LiCoO_2$	Japan
Xstrata	Li-based, Ni-based	Pro-and hydrometallurgy	Cu, Ni, Zn	Switzerland
Onto technology LLC	Li-based	Direct recycling	Cathode	US
Recupyl	Li-based, Zn-based	Hydrometallurgy	$Co(OH)_2$, Li_2CO_3	France
Retriev Technologies	All	Hydrometallurgy	Co, Li_2CO_3	US, Canada
Campine	Pb-acid	Pyrometallurgy	Pb	Belgium
Rockwood Lithium	Li-based	Hydrometallurgy	Oxide (Co, Li)	Germany
Sumitomo and Sony	All	Pro-and hydrometallurgy	Co, Ni, Fe alloy, CoO	Japan
Umicore	Li-based, NiMH	Pro-and hydrometallurgy	$CoCl_2$, $Ni(OH)_2$	US
SNAM	Li-based, Ni-based	Pyrometallurgy	Ni, Co, Cd	France

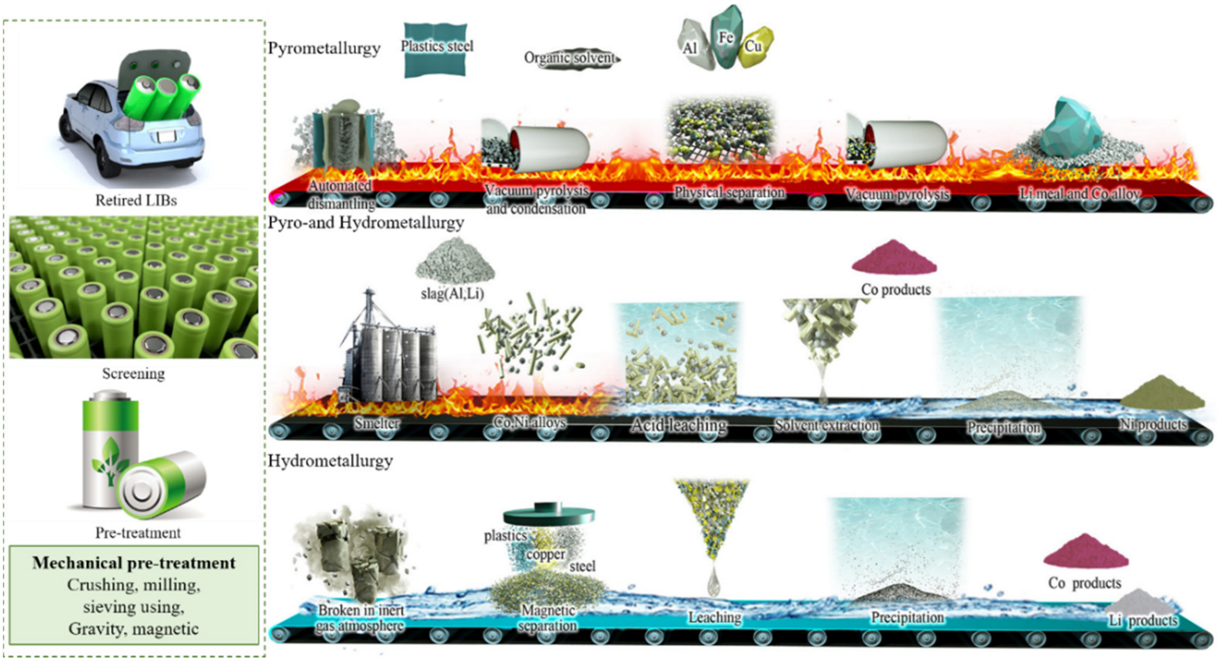

Figure 4. Process flow of industrial recycling method (pyrometallurgical, hydrometallurgical and pro-and hydrometallurgical) of retired power lithium battery (Ref. [1]).

2.2. Echelon Utilization

When the capacity of the power LIBs degrades to about 80% of the rated initial capacity, they can no longer meet the requirements of EVs. That is, they have reached the retirement standard. However, the remaining capacity in the retired power LIBs is still large at this time, and direct recycling may result in a waste of energy. In many scenarios, echelon utilization is more attractive for both the government and investors than direct recycling of materials in retired power LIBs [39]. After re-testing, analysis, screening, and regrouping of retired power LIBs, they can be applied to the fields of microgrids, communication base stations, and energy storage systems. The United States and some European countries have taken the lead in carrying out research on the echelon utilization of retired power LIBs. However, the echelon utilization of retired power LIBs has always been in a state of being difficult to implement and control.

Currently, the echelon utilization of retired power LIBs follows the previous experience and forms a recycling system with the battery manufacturer as the main responsible party [40]. Battery retailers in the US are mandated to recycle retired batteries and to get consumers to recycle retired batteries through a deposit voluntarily. The recycling of retired batteries in Japan is the responsibility of the manufacturers, and the government will issue certain subsidies to increase manufacturers' enthusiasm for recycling. Figure 5 shows the disposal route for the echelon utilization of retired power LIBs. It can be seen from Figure 5 that for the disposal technology of retired power LIBs, the echelon utilization is preferentially considered. In general, the echelon utilization is still in the demonstration application stage. Most of the existing projects are led by automobile companies and carried out in conjunction with battery manufacturing companies and battery recycling companies. Only a few companies have taken the lead in achieving commercial breakthroughs, such as commercial applications in the field of energy storage. Note that the cycle life of LFP is more than 3500 times, and some LFPs can reach 5000 times. Meanwhile, the capacity decays slowly with the increase in cycle times. However, the capacity of NMC or NCA decays to 80%. Then the relative capacity shows a rapid decay trend with the increase in the number of cycles, so the number of echelon cycles is small, and the reuse value is extremely low. Therefore, LFP generally continues to be used as an energy storage battery.

NMC or NCA is more suitable for resource recovery because they can extract metals such as nickel, cobalt, and lithium.

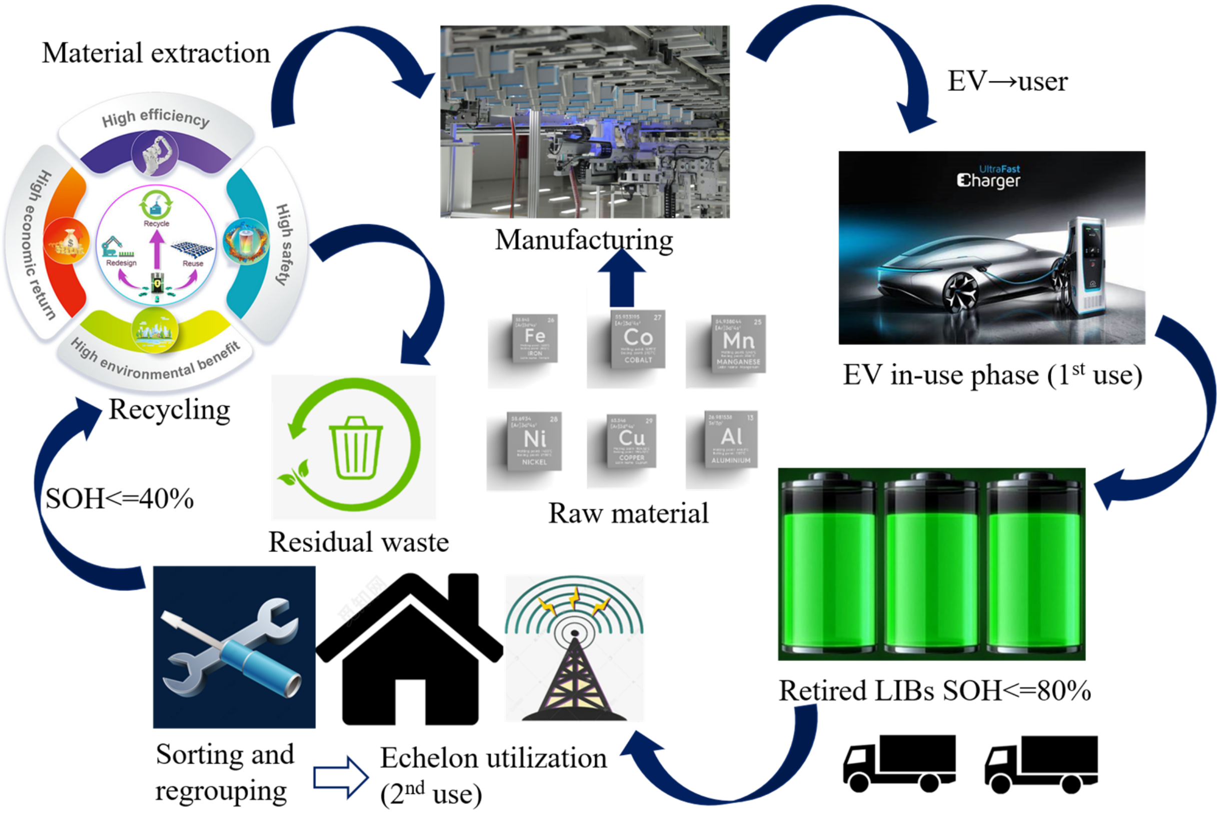

Figure 5. Disposal route for echelon utilization of retired power LIBs.

Figure 6 shows the development process of the echelon utilization of retired power LIBs. 4R Energy has developed a series of household and commercial energy storage products using the retired power LIBs for echelon utilization [41]. The National Renewable Energy Laboratory of the United States has used retired power LIBs for echelon utilization for energy storage and in commercial and residential buildings [42]. ABB has cooperated with General Motors to utilize the power batteries retired from Chevrolet vehicles in cascade and manufacture backup power supplies for household and small commercial use, as well as peak shaving and valley filling equipment matched with clean energy power generation. Toyota has used the retired batteries in its Camry to store and supply energy for the facility. It has also designed a good management system to extend the service life of retired batteries by nearly two times [43–45]. In China, the Beijing Daxing electric taxi charging station echelon utilization demonstration project jointly established by China Electric Power Research Institute, State Grid Beijing Company, Beijing Jiaotong University, and other institutes uses retired batteries to adjust the output power of transformers and maintain stable voltage level. In the communications industry, a Chinese company took the lead in establishing a dismantling and recycling project for discarded EVs, using decommissioned batteries as a reserve power source for equipment such as base stations and street lamps to achieve stability and energy conservation. Enterprises and scientific research institutes are actively exploring and commercializing the advanced technologies of echelon utilization, and echelon utilization is booming worldwide [44–46].

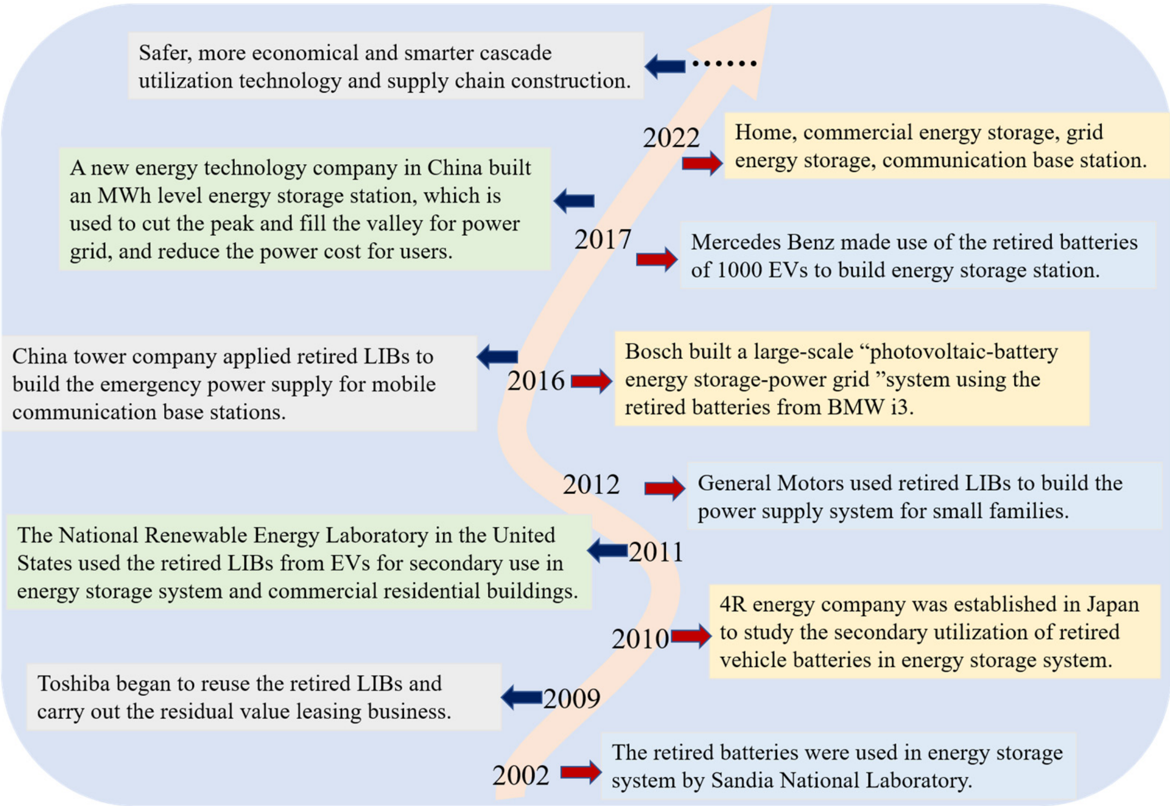

Figure 6. Development of echelon utilization of retired power LIBs [47].

3. Status of Echelon Utilization of Retired Power LIBs

3.1. Performance Evaluation of Retired Power LIBs

The purpose of evaluating the performance of retired power LIBs is to judge whether they have the value of echelon utilization and to apply them to different echelon utilization scenarios according to their performance. For scenarios with high consistency requirements, such as remanufacturing and grid-related energy storage systems, retired power LIBs need to have better performance. For retired power LIBs with lower performance, they can be applied to scenarios with low echelon utilization requirements, such as low-speed EVs, communication base stations, etc. The main performance evaluation methods for retired power LIBs include state of health (SOH) estimation [48], remaining useful life (RUL) prediction [49], electrochemical impedance spectroscopy (EIS) [50], life cycle assessment method [51], etc.

3.1.1. SOH Estimation

SOH can be used to explain the general condition of battery aging and degradation and can also be regarded as an indicator of time. The current research methods for SOH estimation can be mainly divided into three categories. (I) Model-based features: Features should be able to reflect mathematical or physical models well, such as internal resistance, capacity, and open circuit voltage can provide a very intuitive insight for SOH estimation. However, these features also need to be obtained through complex mathematical or physical models, such as circuit and electrochemical models. Figure 7a shows the SOH estimation framework based on model features. (II) Data-driven: With the development of artificial intelligence, features such as internal resistance, incremental capacity, differential voltage, etc., can be mapped to SOH through machine learning or deep learning algorithms. Figure 7b illustrates the SOH estimation process based on data-driven analytical features, which are mainly divided into probabilistic and non-probabilistic models [52]. (III) Battery management system-based raw features. The battery management system can monitor and collect the changes of various characteristic parameters in the whole life cycle of the

LIBs. However, the data collected by the battery management system is noisy, and noise reduction and data cleaning are required before use. Figure 7c shows the SOH estimation process based on the raw feature of the battery management system.

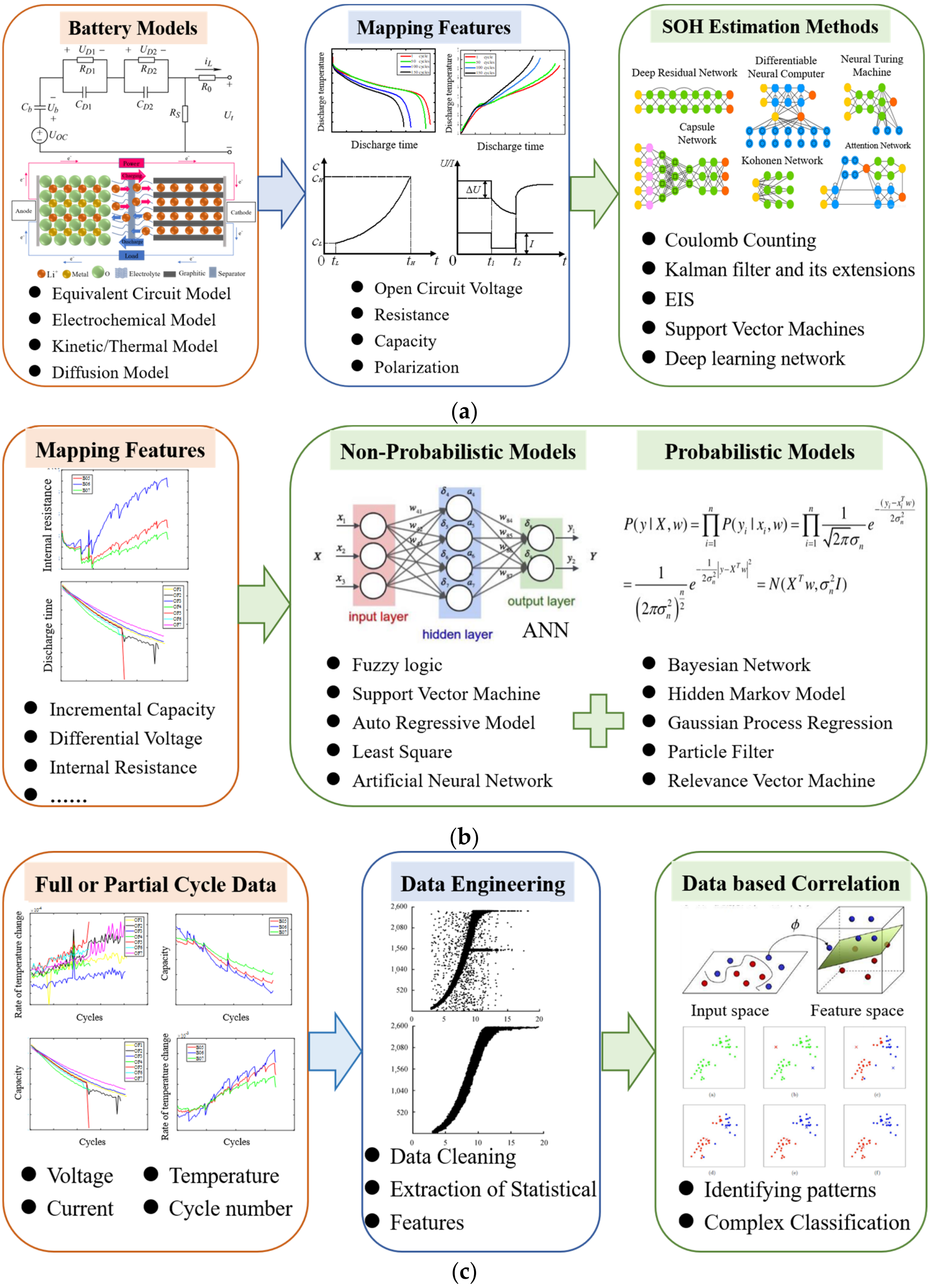

Figure 7. SOH estimation [53]. (**a**) Model-based features for SOH estimation. (**b**) Data-based analytical features for SOH estimation. (**c**) Battery management system-based raw features for SOH estimation.

We provide a review of SOH estimation, as shown in Table 4. Perspectives such as battery type, SOH estimation method, mode of operation, and category are compared in Table 4. The mode of operation is distinguished as online and offline. The classification of relevant studies in Table 4 is largely based on the categories described above.

Table 4. Comparison of related studies on SOH estimation.

Study	Battery Type	Methods	Mode of Operation	Category
Wang et al. [54]	LIBs	Artificial neural network and equivalent circuit model	Offline	I
Hu et al. [55]	LIBs	K-means algorithm and particle swarm optimization	Offline/Online	II
Patil et al. [56]	LIBs	Support vector machines	Offline/Online	III
Ng et al. [57]	LIBs	Naïve Bayes model	Online	II
Galeotti et al. [58]	Lithium polymer batteries	EIS	Offline	I
Song et al. [59]	LIBs	Artificial neural network	Offline	III
Jia et al. [60]	LIBs	Gaussian process regression	Online	II
Kaur et al. [61]	LIBs	Feed-forward neural network and convolutional neural network, and long short-term memory neural network	Online/Offline	III
Eddahech et al. [62]	LIBs	EIS and Neural Network	Offline/Online	I

3.1.2. RUL Prediction

Similar to SOH estimation, RUL prediction is also an important indicator to measure the health status of retired power LIBs. The RUL of retired power LIBs can reflect the degree of degradation or aging of LIBs. In the stage of echelon utilization of retired power LIBs, only by mastering the information of RUL can it be safely guaranteed to work in specific scenarios and be replaced regularly. Therefore, the RUL prediction for retired power LIBs is quite critical. The commonly used RUL prediction methods can be roughly divided into model-based, data-driven, and hybrid-driven prediction methods [63,64]. Model-based RUL prediction methods are mainly modeled according to the battery degradation mechanism. The commonly used models include electrochemical, ECM, and empirical models. Figure 8 is the flowchart of the model-based RUL prediction method. With the development of artificial intelligence and big data, data-driven RUL prediction methods are widely used. Data-driven methods use mathematical statistical theory and machine learning techniques to directly map a predictive model between features and RUL. Unlike the model-based RUL prediction method, the data-driven method has many applications and good universality. The flowchart of the data-driven RUL prediction method is shown in Figure 9. Hybrid-driven approaches combine the strengths of model-based and data-driven approaches. Hybrid-driven approaches can overcome the problem that the training time of the data-driven approach is too long, and it can also make up for the problem of the low accuracy of the model-based approach. The hybrid-driven approach is further divided into model-data hybrid-driven and data-data hybrid-driven. Figure 10 is the flowchart of the hybrid-driven prediction method.

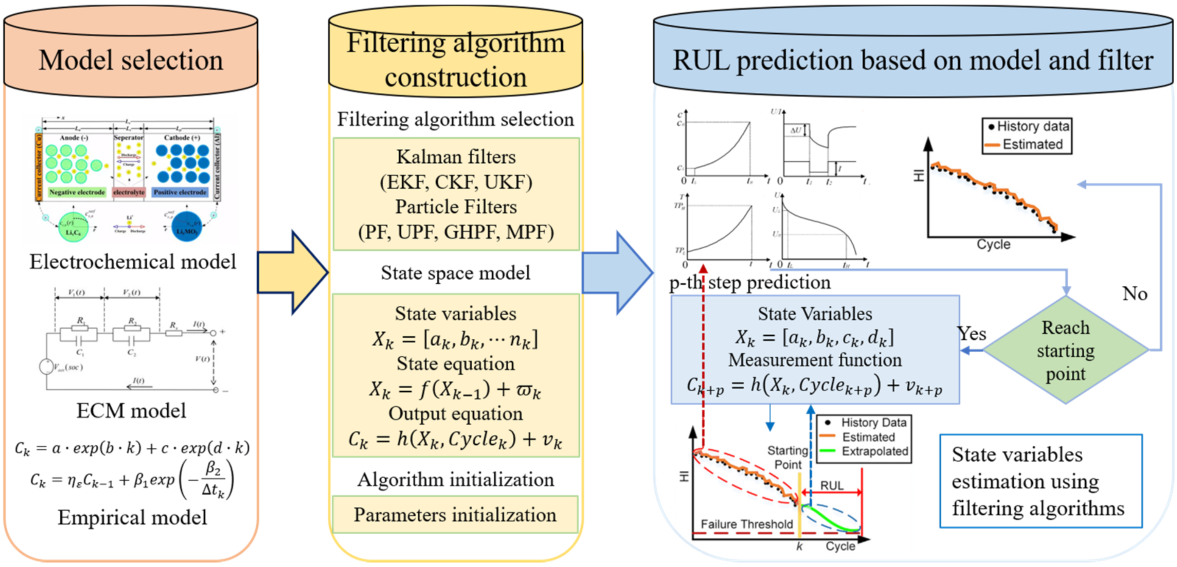

Figure 8. Framework for the model-based approach of RUL prediction.

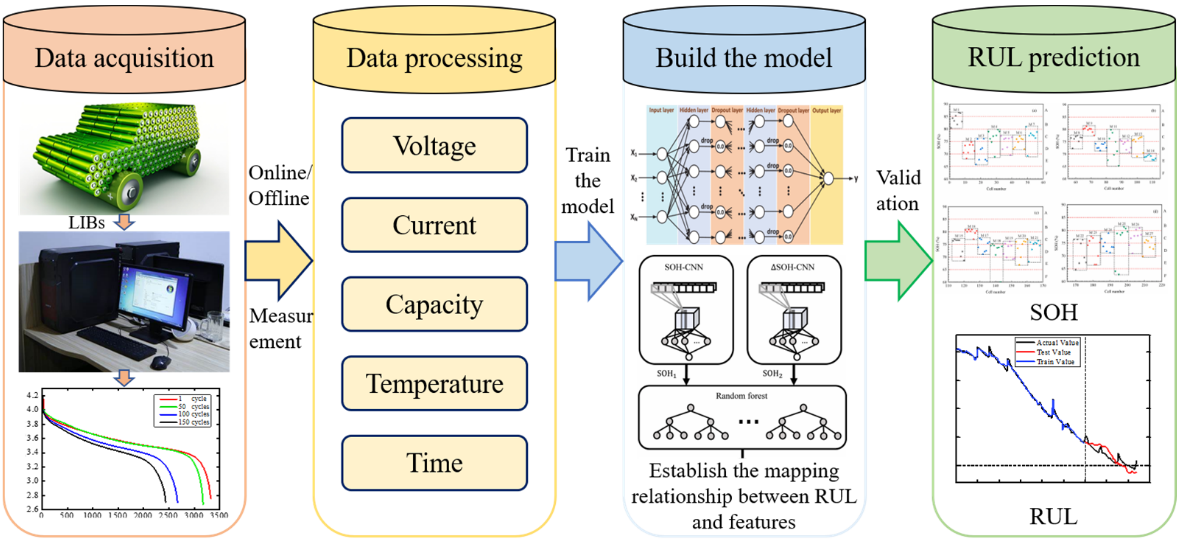

Figure 9. Framework for the data-driven approach of RUL prediction.

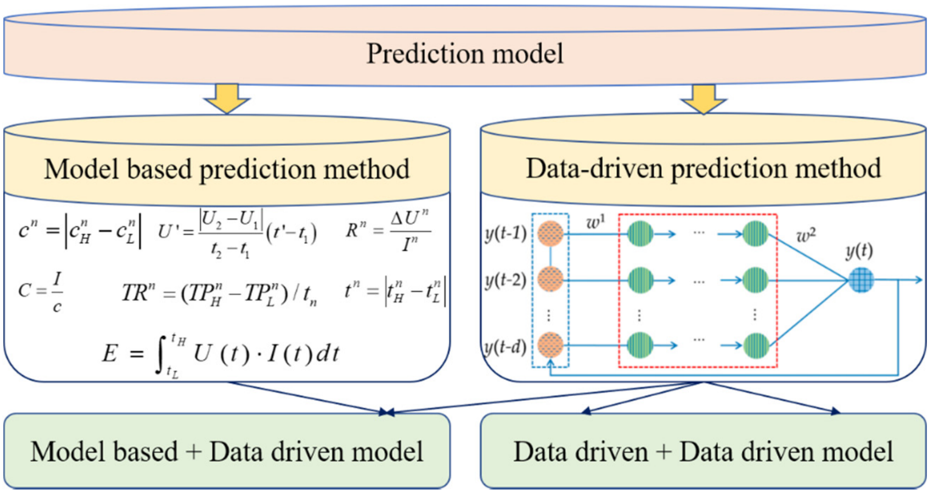

Figure 10. Framework for the hybrid-driven approach of RUL prediction [65].

The data-driven method is the most generally used among the above three categories. Data-driven methods mainly use historical data to predict the aging trend of batteries. In many cases, the data-driven model is a black-box model. Although the data-driven method does not need to establish a complex mechanism model, the collection process of historical data is also a heavy task. We have reviewed related studies on RUL prediction, as shown in Table 5. We mainly compare the current research in terms of battery types, RUL prediction health indicators, RUL prediction methods, and advantages and disadvantages.

Table 5. Comparison of related studies on RUL prediction.

Study	Battery Type	Health Index	Methods	Advantages	Disadvantages
Ng et al. [57]	LIBs	Capacity	Naive Bayes	Concise	Based on attribute independence assumption
Pattipati et al. [66]	Rechargeable battery	Capacity, internal resistance	Support vector machine	Unaffected by nonlinearities and small samples	Need to satisfy Mercer criterion
Wang et al. [67]	LIBs	Energy efficiency, temperature	Support vector regression	Fewer dimensions	Lack of sparseness
Zhou et al. [68]	LIBs	Mean voltage drop	Relevance vector machine	Avoids overfitting and underfitting	Not suitable for long-term prediction
Richardson et al. [69]	LIBs	Capacity	Gaussian process regression	Unaffected by high-dimension and small samples	Parameter and kernel function selection is sensitive
Zhang et al. [70]	LIBs	Capacity	Long short-term memory recurrent neural network	Avoids overfitting and underfitting	Requires sufficient historical data
Liu et al. [71]	LIBs	Capacity, discharging voltage difference	Monotonic echo state networks	Strong nonlinear processing ability	High computational complexity
Pang et al. [72]	LIBs	Capacity	Wavelet decomposition technology and neural network	Not affected by prediction starting points	Relatively complex model
Wang et al. [73]	LIBs	Capacity and 13 features	Bayesian model averaging	High prediction accuracy	An encoding network is required
Mao et al. [74]	LIBs	Capacity	Machine learning algorithms	Not affected by prediction starting points	Complex model fusion

3.1.3. EIS

EIS is a powerful non-invasive detection technique widely used in the study of electrochemical system aging [51]. EIS can get the corresponding response by adding current or voltage to the system to be measured. EIS has been widely used to characterize battery features, such as LIB materials [75], state of charge [76], SOH, charge transfer impedance, capacity loss mechanisms [77,78], and charge and discharge temperature. In order to reduce the inconsistency within the battery pack or prepare for the cascade utilization of retired power LIBs, the capacity measurement of LIBs is very necessary. Schuster et al. [79] analyzed and evaluated the relationship between the capacity and impedance of LIBs. Guo et al. [80] proposed a novel method to estimate the differential capacity. They demonstrated that the differential capacity could be used to estimate the SOH of LIBs, which is very promising. Mingant et al. [81] proposed establishing quasi-EIS from voltage and current signals, then developed a SOH prediction algorithm based on the established EIS. Oldenburger et al. [82] used EIS to measure the Warburg impedance at low and even ultra-low frequencies for three different types of LIBs. They conducted a detailed study of the factors that affect the Warburg impedance. The above studies indicate that the correlation between impedance parameters can be used to quickly estimate battery capacity, state of charge, SOH, and lifetime.

The application of EIS on batteries also provides new ideas and methods for classifying and reorganizing retired power LIBs [83]. However, EIS is thoroughly affected by fluctuations in the state of charge, state of health, charge-discharge rate, and temperature. The current dilemma is how to assess the health of retired power LIBs while avoiding the influence of these factors quickly and accurately. EIS requires specialized equipment to obtain, which is very expensive. It is quite time-consuming to conduct large-scale screening of retired power LIBs, which also increases the cost. Therefore, the economic problem is also a critical issue faced by EIS applications [84]. Some scholars attempt to make breakthroughs in sorting equipment, testing procedures, and artificial intelligence algorithms. Intelligent algorithms such as machine learning are widely used to classify and reorganize large-scale retired power LIBs. The emergence of new technologies such as digital twins has also enabled massive battery data to be uploaded to the cloud. Therefore, much historical data on retired power LIBs could be collected in the future. These historical data in the cloud can also be used to investigate the performance of retired LIBs, which may inherit EIS as a more direct and economical way to estimate the status of retired power LIBs. Overall, using EIS for sorting and regrouping retired power LIBs is likely to be an adjunct in the future [85].

3.2. Sorting and Regrouping Methods of Retired Power LIBs

After extracting the performance evaluation indicators of retired power LIBs, selecting an appropriate classification or clustering algorithm is necessary to classify and reorganize retired power LIBs. With the development of artificial intelligence, machine learning has shown significant advantages in solving classification or clustering problems [86]. Common clustering algorithms show superiority in solving low-dimensional problems but will increase the algorithm's complexity in high-dimensional problems. Therefore, considering the application scenario, the classification dimension should be reduced to reduce the algorithm's computational complexity and improve the classification's efficiency and accuracy. Figure 11 manifests a typical sorting and regrouping process of retired power LIBs. LIBs retired from EVs need to undergo a series of operations such as detection, clustering, and reorganization to complete the echelon utilization. First, it is necessary to evaluate the performance of retired power LIBs, and eliminate retired power LIBs that do not meet the echelon utilization. Then the required feature factors for regrouping need to be extracted and clustered based on machine learning algorithms. Finally, according to the performance of different groups after clustering, different echelon utilization scenarios are matched for retired power LIBs. The discrepancies in the manufacturing state of power LIBs, such as differences in capacity, internal resistance, and Coulomb efficiency, will deteriorate in the echelon utilization after their retirement [87]. Through a series of operations such as sorting and regrouping, the consistency of the battery pack has been improved, which can ensure the safety performance and improve the service life of retired power LIBs when used in a cascade [63,88].

We have reviewed related studies on sorting and regrouping methods, as shown in Table 6. We mainly compare the current research in terms of battery types, parameters, sorting and regrouping methods, validation methods, and advantages of the study. It can be seen from Table 6 that the characteristic parameters selected for sorting and regrouping of the current research mainly include capacity, voltage, internal resistance, temperature, RUL, EIS, etc. In terms of the sorting and regrouping methods used in the current research, classification and clustering algorithms such as K-means, support vector machine, neural network, etc., are more common.

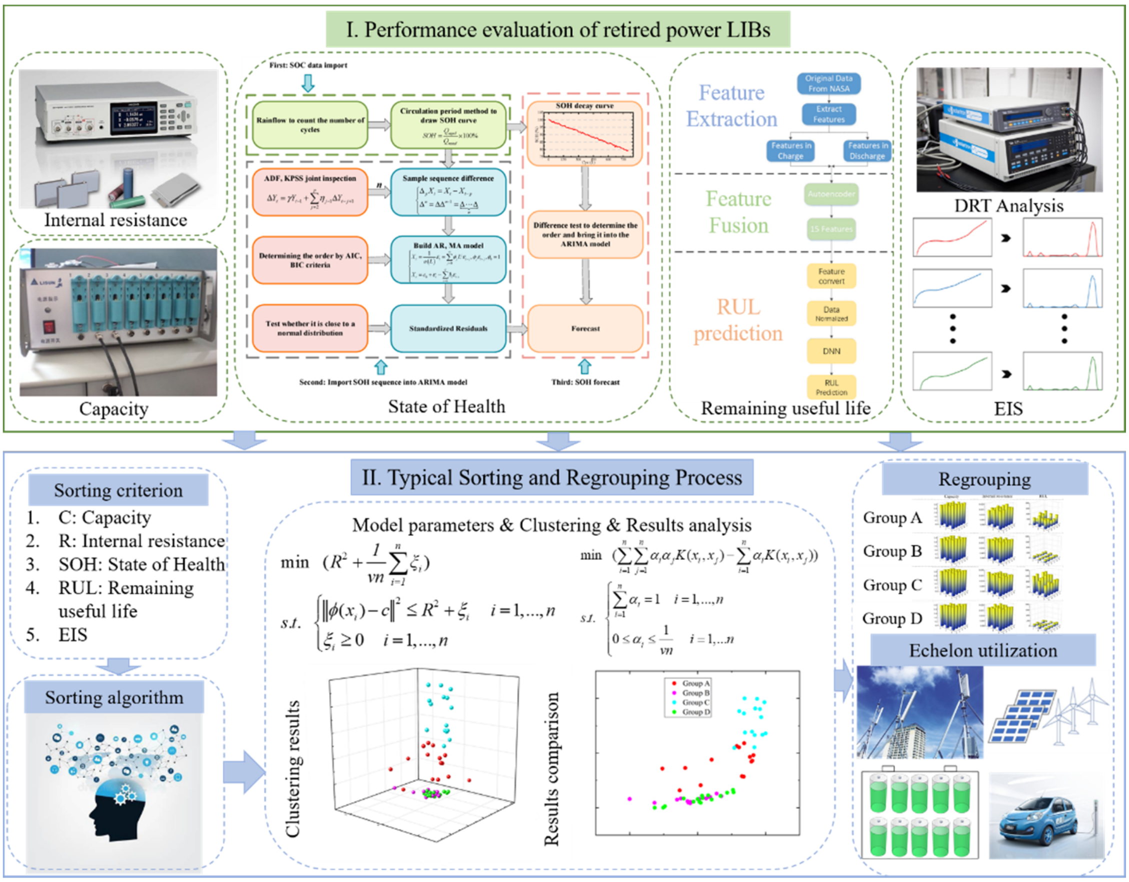

Figure 11. A typical sorting and regrouping framework for retired power LIBs [89].

Table 6. Comparison of related studies on sorting and regrouping methods.

Study	Battery Type	Parameters	Sorting/Regrouping Methods	Validation Methods	Advantages
Liao et al. [90]	Li-ion phosphate batteries	Capacity, voltage, resistance, EIS	Capacity, pulse discharge voltage, charge transfer resistance, and lithium-ion diffusion coefficient	Experiment	No special equipment, high economy
Li et al. [91]	Li-ion phosphate batteries	Capacity, equivalent resistance spectrum	Difference of 2% of the maximum capacity	Experiment	Convenient and efficient
Lai et al. [92]	LIBs	Capacity, voltage, internal resistance	Neural network model and the piecewise linear fitting model	Experiment	High efficiency
Jiang et al. [93]	LIBs	Capacity, resistance	K-means algorithm	Simulation	Preferable consistency, high capacity utilization

Table 6. *Cont.*

Study	Battery Type	Parameters	Sorting/Regrouping Methods	Validation Methods	Advantages
Li et al. [89]	LIBs	Capacity, internal resistance, RUL	Novel equal-number support vector clustering algorithm	Simulation	Equal-number, preferable consistency
Lai et al. [94]	LIBs	Capacity	K-means algorithm	Simulation, Experiment	High precision and consistency
Zhou et al. [95]	$LiFePO_4$ battery	Capacity, resistance	Support vector machine	Experiment	High classification accuracy
Garg et al. [96]	All	Capacity, internal resistance	Self-organizing maps	Experiment	Reduced inconsistencies within the battery pack
He et al. [97]	$LiFePO_4$ battery	Temperature, capacity	Self-organizing maps	Simulation	High consistency
Yang et al. [98]	Power battery	Resistance, open circuit voltage, capacity	Combination of k-means and genetic algorithm	Experiment	Better applicability

4. Echelon Utilization Scenarios and Economy of Retired Power LIBs

4.1. Echelon Utilization Scenarios of Retired Power LIBs

The echelon utilization scenarios of retired power LIBs are also diverse and can be divided into static and dynamic application scenarios. Many typical static scenarios exist for the echelon utilization of retired power LIBs, such as energy storage systems, communication base stations, and microgrids [45,99–101]. The typical dynamic scenarios of echelon utilization of retired power LIBs are mainly the power source of low-speed vehicles, such as low-speed vehicles, electric bicycles, and urban sanitation vehicles [102]. A typical echelon utilization scenario of retired power LIBs is shown in Figure 12. Retired power LIBs have good market prospects and echelon utilization scenarios, such as communication base stations, low-speed EVs, energy storage stations, and renewable energy systems. In terms of scale, there are currently two main technical routes for the echelon utilization of retired power LIBs: (i) cell-level echelon utilization and (ii) module-level echelon utilization. The cell-level echelon utilization mainly disassembles the retired power LIB module into a single cell. Then its performance indicators such as capacity, internal resistance, and SOH are measured by special equipment or means. Finally, they are sorted and used in different scenarios based on sorting and regrouping methods [92]. Module-level echelon utilization is to directly evaluate the performance of retired power LIB modules, then directly classify and reorganize them according to their performance, and finally apply them to different echelon utilization scenarios [103].

Due to the production process, manufacturing errors, and other reasons, it is inevitable that there will be differences in the performance of a single cell in the battery module. Currently, technical route (i) is an ideal choice. Technical route (i) disassembles the retired power LIB module and then applies it to different echelon utilization scenarios, which reduces the inconsistency within the group and is widely used. However, the technical route (i) requires a lot of manpower and time, which will cause problems of efficiency and economy of echelon utilization. With the continuous improvement of the production process of LIBs, the manufacturing accuracy and performance consistency of the LIBs have also been significantly refined. That is, the performance difference of a single battery in the module has been continuously reduced. The optimization and improvement of the process provide the possibility for applying the technical route (ii). Technical route (ii) does not require dismantling retired power battery modules, so labor and time costs can be saved, thereby improving efficiency and economic benefits. Therefore, the technology route (ii) is becoming the mainstream development direction of the echelon utilization of retired power LIBs. However, it is undeniable that there are still many challenges in echelon utilization, which we will review in Section 5.

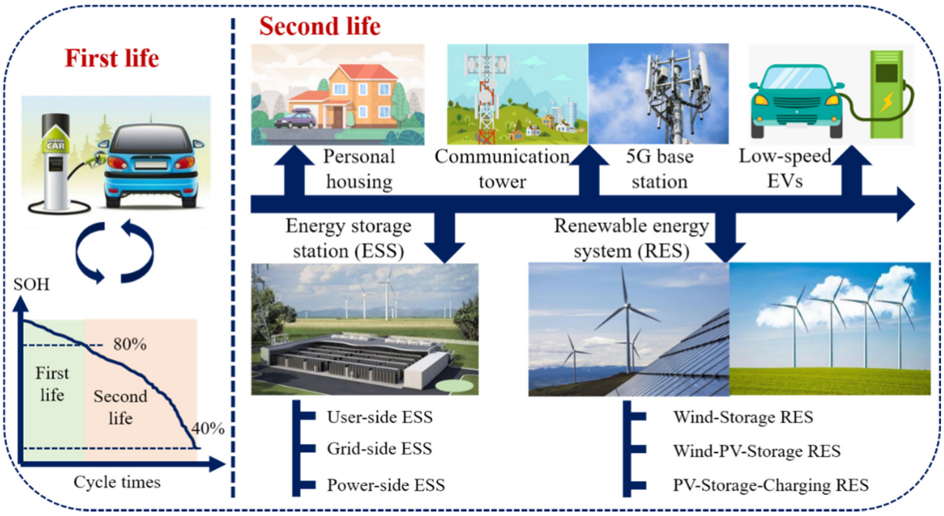

Figure 12. Typical echelon utilization scenarios of retired power LIBs.

4.2. Echelon Utilization Economy of Retired Power LIBs

With the reduction of raw material costs, the improvement of process technology, and mass production, the cost price of LIBs is also falling, but LIBs still account for a large proportion of the total EV price [104]. For the echelon utilization of retired power LIBs, cost and economic analysis must be done first to ensure that investors truly recognize profitability. Economic analysis should be evaluated from the perspective of cost and benefit. Although some milestone projects or models have been developed, the high cost of echelon utilization limits their application, making the economics of these projects or models questionable. Figure 13 reviews the composition of the costs and benefits of the echelon utilization of retired power LIBs [42,105]. It is not difficult to find from Figure 13 that the economic analysis cannot just compare the cost of new and retired batteries.

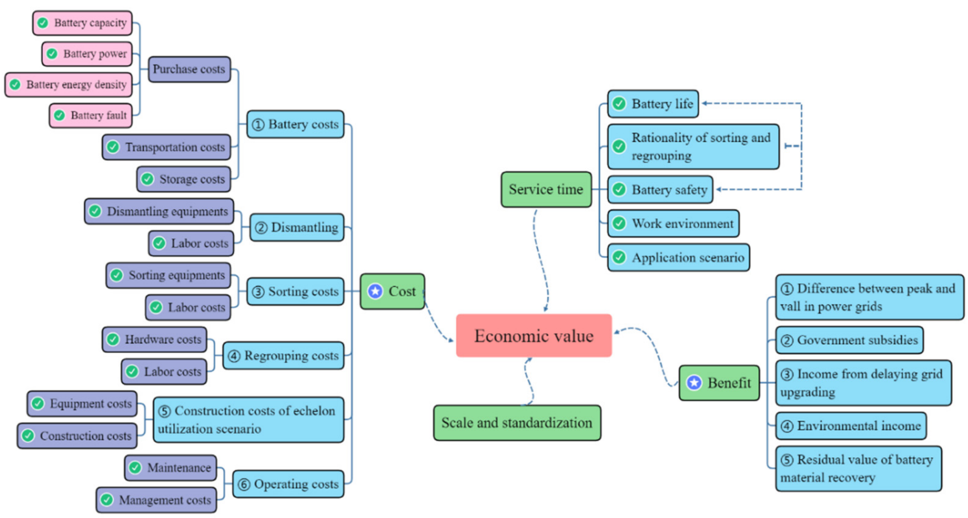

Figure 13. The composition of the cost and benefit of the echelon utilization of retired power LIBs [106].

The National Renewable Energy Laboratory of the United States has developed a model for evaluating the cost of echelon utilization of retired power LIBs. The model of this study shows that the total cost of the echelon utilization of retired power LIBs is 44 $/kWh, which includes two parts: the battery cost of 20 $/kWh and the cascade utilization cost of 24 $/kWh [107]. Zhan et al. [108] proposed a decommissioned power LIBs wind energy storage system, in which economic performance was emphasized. Taking a 21 MW wind farm as the object, the scenario-based stochastic planning method is adopted. The results show the economic feasibility of the retired power LIBs in the wind farm scenario. Casals et al. [109] consider demand response services to use retired power LIBs for building scenarios in terms of economics and aging performance. The findings suggest that using retired power LIBs for residential use may not be the most economical option, and may be used in the secondary electricity market in the future. It recommends manufacturers consider ecological issues in their design stage.

At present, the research on the economics of echelon utilization of retired power LIBs is mainly based on the modeling of costs and benefits based on application scenarios. Gur et al. [110] studied the economics of retired power LIBs for stationary energy storage systems and simulated the net present value of four different systems. The results show that compared with other countries, Germany's echelon utilization of retired power LIBs is more meaningful. The government is suggested to introduce more policies to encourage investment in the echelon utilization system of retired batteries. Lih et al. [111] proposed that the echelon utilization of retired power LIBs based on the environmental 3R principles (recycle, reuse, reduce) can bring long-term stable economic benefits. Tang et al. [112] applied the reward and punishment mechanism to the field of retired power LIB recycling and echelon utilization. They established a game theory model and studied the economic impact of the retired power LIB echelon utilization under the reward and punishment mechanism. The results show that compared with no policy intervention and subsidy mechanism, the reward and punishment mechanism has more significant advantages in reducing the environmental burden. However, the economic analysis of the echelon utilization of large-scale retired power LIBs needs to be carried out from multiple dimensions and multiple aspects, and the current research is rarely involved.

5. Technical Challenges of Echelon Utilization

Although the echelon utilization of retired power LIBs has great development prospects and development potential, there are still many technical challenges [113,114]. The process of echelon utilization of retired power LIBs is very complicated, and the recycling and reorganization processes are also different for different echelon utilization scenarios. Currently, the main challenges of echelon utilization mainly include safety issues, performance evaluation methods, economic feasibility, supply chain construction, and regulation and certification.

5.1. Safety Issues

The retired power LIBs themselves have been cycled to the retirement standard under various working conditions, so the safety of their echelon utilization is undoubtedly one of the key technical challenges they face. The safety management of the full life cycle of retired power LIBs is the main concern of the current research [115]. If the safety of the echelon utilization cannot be guaranteed, it may cause thermal runaway or even more serious disasters [116,117]. We know that many side reactions will occur in the aging process of batteries, and these side reactions are not easily exposed but can cause great harm. The occurrence of these side reactions probably causes the internal short circuit of the battery to cause thermal runaway and more serious safety problems [118,119]. The echelon utilization will aggravate the aging of the retired power LIBs and cause the superposition of the internal side reactions of the battery, so the safety problem of the echelon utilization is more prominent.

Currently, research on the echelon utilization of retired power LIBs mainly focuses on classification and recombination methods to reduce the intra-group inconsistency of LIBs, and few studies focus on the chemical reactions inside the batteries. However, to ensure the safety of retired power LIBs in different scenarios, it is necessary to evaluate the side reactions inside the batteries during screening. The decisive technical challenge is how to efficiently and accurately establish a model that can quickly evaluate these side reactions and combine it with digital twin technology to monitor the internal conditions of retired power LIBs effectively. This will prevent the deterioration of battery safety during use. Therefore, an efficient and robust life cycle battery management system is necessary. Retired power LIBs will also generate a lot of heat during use, and it is also necessary to design a battery thermal management system with efficient heat dissipation [116,120,121].

5.2. Performance Evaluation Methods

The performance evaluation method is mainly to obtain the performance parameters of the retired power LIBs, which can evaluate whether the retired power LIBs have the value of echelon utilization and prepare for screening and regrouping. Retired power LIBs with better performance can be used in scenarios with strict conditions, such as remanufacturing, low-speed EVs, or microgrids. On the contrary, retired power LIBs with poor performance may be used in other scenarios with low requirements. Currently, the performance evaluation methods of retired power LIBs mainly include SOH estimation, RUL prediction, and EIS [27]. There are differences in power LIBs due to inconsistencies during production. During use, the differences will be further expanded due to the number of cycles and the user's driving habits, which leads to the vastly different performance of retired power LIBs. The difference in performance will lead to various performance evaluation indicators, which also greatly complicates the echelon utilization.

Using simple and high-precision means to accurately evaluate large-scale retired power LIBs has become an elemental issue for echelon utilization. In the process of industrialization of large-scale echelon utilization of retired power LIBs, the robustness and generalization ability of the model should be improved, and efforts should be made on the aging mechanism and application scenarios of batteries. Thanks to the development of information technology, the battery management system can obtain battery health parameters such as voltage, current, and temperature, which provides convenience for evaluating the performance of retired power LIBs. In terms of SOH estimation and RUL prediction, it is necessary to integrate multiple artificial intelligence algorithms to improve the prediction accuracy and the model's generalization performance. In the future, we can easily build a cloud-based online battery monitoring and management system based on big data, artificial intelligence, and data mining. Using battery data stored in the cloud, data-driven performance evaluation methods for retired power LIBs will no longer be a problem. Therefore, the data-driven or hybrid data-driven performance evaluation method of retired power LIBs will become the development direction of evaluating LIBs for echelon utilization through cloud data [122].

5.3. Supply Chain Construction

In addition to breaking through technical challenges, the large-scale echelon utilization of retired power LIBs also needs to build a complete supply and demand chain. The construction of the supply and demand chain of retired power LIBs can be divided into two modes. (a) The automobile or battery manufacturers are the main body to integrate various resources, give full play to the advantages of science and technology, and implement the supply chain construction of echelon utilization, such as General Motors and BYD. (b) Another model is to rely on industry, government, or third-party organizations to build a supply and demand chain for the echelon utilization of retired power LIBs. Since the supply chain needs to be completed by multiple units, the supply and demand chain that benefits all participants has not yet been constructed. The government should also introduce policies to encourage enterprises to promote the echelon utilization of retired power LIBs.

To build a retired power LIBs supply chain that can be successfully applied to industry, we also need to solve many problems in the recycling, dismantling, screening, reorganization, installation, and maintenance of retired power LIBs. The recycling process is difficult for large-scale echelon utilization due to the different types and materials of batteries. Dismantling and screening require specialized equipment and a work environment to ensure safety. After reorganization, large inconsistencies in the battery pack will also cause large differences in battery modules, which is not conducive to high-performance echelon utilization scenarios. In addition, there is a lack of sharing of battery information among various processes, which also hinders the process of echelon utilization of retired power LIBs. In the future, we will use technologies based on big data and artificial intelligence to help standardize batteries or battery modules. At the same time, the battery production process was improved to reduce performance differences, and relevant policies were introduced to facilitate the echelon utilization of retired power LIBs [123].

5.4. Regulation and Certification

In fact, some effective echelon utilization technologies have been proposed in recent years, and some research projects on echelon utilization of retired power LIBs have also been carried out. However, some technologies have not been widely promoted and adopted due to the lack of professional regulations and certification. Without relevant regulations and certifications, even if an effective echelon utilization technology is developed, it is difficult to be promoted and recognized by consumers. There is a lack of industry guidelines for echelon utilization related technologies such as SOH estimation and RUL prediction for small and medium-sized enterprises. In dismantling and screening retired power LIBs, there is currently no unified standard, and relevant regulation and certification still need to be improved. In addition, due to differences in battery models, there is no uniform standard and certification for battery coding, loading, and data interaction of battery health status data, which also hinders the development of cascade utilization. In the future, introducing regulations and certification for the full life cycle of batteries will effectively promote the development of the global retired power LIBs echelon utilization industry [124].

6. Future Research Outlooks

In the foreseeable future, LIBs will remain the first choice for EVs. In recent years, with the increasing number of EVs, the scale of retired power LIBs is huge, and the problem of echelon utilization has become a research hotspot. Many governments and institutions are also introducing relevant policies to improve the industrial supply chain. Green economy and environmental protection are the themes of current world development, and echelon utilization schemes and scenarios also emphasize economic and environmental protection issues. Whether in terms of industrial scale or economic benefits, the echelon utilization of retired power LIBs undoubtedly has development potential and prospects. In the future, the screening and reorganization of retired power LIBs should be carried out quickly, efficiently, and reasonably from the perspective of technical means to ensure the safety and efficiency of echelon utilization. As shown in Figure 14, the prospect of LIBs life cycle utilization. Specifically, the echelon utilization of retired power LIBs will have the following development directions:

(1) Full life cycle battery management system for LIBs based on the digital twin and big data. The collection of historical data through communication technology during the service life of LIBs can provide resources for evaluating retired power LIBs. For retired power LIBs, key data that can be used to evaluate or predict LIBs can be mined from massive historical data using big data and machine learning. A key technical problem is how to quickly mine variable state quantities from massive and diverse data and use prediction functions to build accurate sorting models.

(2) Scenario planning method for echelon utilization of retired power LIBs. Combining the characteristics of the echelon utilization requirements of different scenarios and the evolution law of the performance state of retired power LIBs, a definition mechanism of retired power LIBs and application scenarios is constructed through fuzzy theory, and then the scenarios are pre-allocated.

(3) Economic research on echelon utilization of retired power LIBs. Considering the cost and benefit differences of retired power LIBs in different application scenarios, a high-fidelity model of the cost and benefits of retired power LIBs in different application scenarios is established. Based on the artificial intelligence algorithm, the economic optimization model of the echelon utilization of retired power LIBs is optimized.

(4) The battery life cycle information management and control system based on blockchain technology creates a true, transparent, comprehensive battery traceability system. Solve the problems in constructing battery recycling channels, constructing the whole life cycle recycling evaluation system, and establishing the service system. Combining the characteristics of decentralization and information traceability of blockchain technology. A recycling system for retired power LIBs based on blockchain technology constructed from the aspects of the recycling system framework, recycling operation process, and implementation methods.

(5) To promote the recovery and reuse of retired power LIBs, the production and manufacture of LIBs should be facilitated. LIB models, interfaces, communication protocols, data transmission, etc., should be standardized to facilitate the echelon utilization of large-scale retired power LIBs. An important trend in the future is that the design, production, and manufacturing of LIBs will also become part of battery life cycle management.

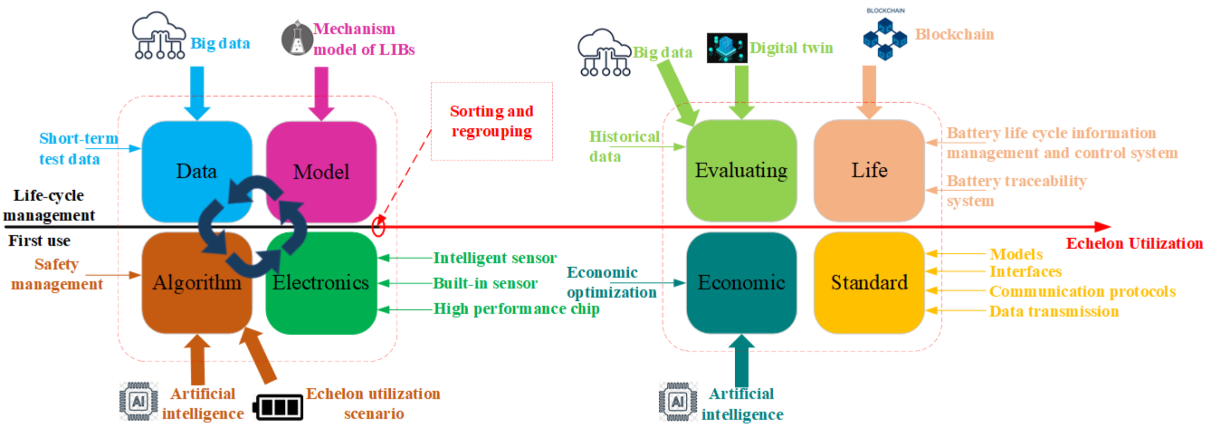

Figure 14. Prospects for full life cycle utilization of LIBs.

7. Conclusions

The rapid development of EVs and the large-scale use of LIBs mean that the echelon utilization of retired power LIBs is an urgent problem that needs to be solved and has huge market prospects. How to deal with large-scale retired power LIBs safely and environmentally has become an urgent problem to be solved. This study comprehensively reviews the challenges and prospects of the echelon utilization of retired power LIBs. The echelon utilization process and cardinal technologies of retired power LIBs are analyzed and summarized. The main conclusions of this work are summarized as follows:

(1) In many scenarios, echelon utilization is more attractive for both the government and investors than direct recycling of materials in retired power LIBs. The echelon utilization of retired power LIBs still faces many difficulties and has been in a state of difficulty in implementation and control. The government should introduce more policies to encourage echelon utilization, and more importantly, it is necessary to break through the cardinal technology of echelon utilization of retired power LIBs.

(2) The purpose of evaluating the performance of retired power LIBs is to judge whether they have the value of echelon utilization and to apply them to different echelon utilization scenarios according to their performance. Commonly used methods are mainly model-based, data-driven, and data-model hybrid. With the development of big data and artificial intelligence, data-based methods are being widely used.
(3) The echelon utilization scenarios of retired power LIBs are also diverse, and this study summarizes them into static and dynamic application scenarios. The cost and economy of echelon utilization are related to whether it can be applied in large-scale industrialization. The economic analysis of the echelon utilization of large-scale retired power LIBs needs to be carried out from multiple dimensions and aspects, and the current research is rarely involved.
(4) The main technical challenges of echelon utilization include safety issues, performance evaluation methods, economic feasibility, supply chain construction, and regulation and certification. Breaking through these key technical challenges can promote the commercialization of echelon utilization.
(5) In the foreseeable future, the development direction of echelon utilization includes: (i) A complete life cycle battery management system for LIBs based on digital twin and big data. (ii) Scenario planning method for echelon utilization. (iii) Economic research on echelon utilization. (iv) A battery life cycle information management and control system based on blockchain technology. (v) Standardization of the models, interfaces, communication protocols, data transmission, etc., of LIBs.

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