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Residual capacity estimation and consistency sorting of retired lithium batteries in cascade utilization process: a review

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Abstract

With the rapid popularization of new energy vehicles worldwide, the demand for power lithium-ion batteries has surged. Consequently, the industry is now facing the challenge of a large number of retired lithium batteries. As these batteries reach the end of their life cycle, efficiently utilizing their residual value has become a key issue that needs to be resolved. This paper reviews the key issues in the cascade utilization process of retired lithium batteries at the present stage. It focuses on the development status and existing challenges of residual capacity estimation methods and consistency sorting technology. Based on the review, this paper also looks forward to the future research trend of the cascade utilization technology of retired batteries, and the efficient cascade utilization of retired lithium batteries will not only alleviate the pressure on resources but also play a positive role in realizing the goal of carbon neutrality and promoting the development of green economy.

Keywords: Retired lithium batteries, cascading utilization, residual capacity estimation, consistency sorting

INTRODUCTION

With the massive use of fossil fuels, the global energy and environmental crises are worsening[1,2]. To promote green and sustainable development, new energy-electric vehicles have become an effective means of energy saving and emission reduction by replacing fuel vehicles. In recent years, as electric vehicles have continued to improve in functionality and comfort, an increasing number of consumers are choosing them as their preferred means of transportation. According to data published by the International Energy Agency, electric vehicle sales worldwide have shown a significant growth trend since 2012, with an additional 3 million electric vehicles expected to be sold in 2024 compared to 2023[3]. Figure 1 illustrates global electric vehicle sales from 2012 to 2024. With the widespread use of electric vehicles, lithium-ion batteries - core power components - will face the issue of "retirement". According to IEEE Standard 1188-1996, when the remaining capacity of a power battery falls below 80% of its factory-rated value, it is considered to have reached the end of its life. With an average of five years of optimal life statistics of electric vehicle power batteries, it is expected that by 2025, the total amount of retired lithium batteries in China will reach 1 million tons[4]. If decommissioned batteries are not properly recycled and utilized, it will result in serious resource waste and environmental pollution. Therefore, effective recycling and reuse of decommissioned batteries helps alleviate the pressure on resources and the environment and is also an important step in promoting green energy cycles and sustainable development.

At present, the treatment of retired power batteries is mainly divided into two directions: recycling and cascade utilization. Recycling is to physically or chemically dismantle the batteries to recover the metal materials with high utilization value. However, decommissioned power batteries still retain about 80% of their original residual capacity, and direct dismantling of these decommissioned batteries will greatly waste their residual value. Therefore, considering that retired batteries still have some economic value in other application scenarios, cascading utilization is an effective way to reuse retired batteries. In the process of cascade utilization, retired power battery packs are first split into individual modules and cells, and then through preliminary sorting and performance testing, the cells with better performance consistency are sorted out and reassembled into new battery modules. These recombined modules can be used for grid storage, communication base stations, low-speed electric vehicles, and other scenes with good working conditions and low battery performance requirements[5]. The cascade utilization not only maximizes the residual value of retired power batteries and extends the overall life of the batteries, but also plays a significant role in promoting the green and sustainable development of the electric vehicle industry. Cascade utilization is a circular, low-carbon way of production and life, which effectively promotes resource conservation and environmental protection. The schematic diagram of the whole process of power battery from retirement to the cascade utilization is shown in Figure 2.

Before cascade utilization of retired batteries, key indicators such as internal resistance, residual capacity, and residual life must be assessed and then consistently sorted to improve the reliability and safety of the battery pack in subsequent use. Among the key indicators for evaluating retired batteries, residual capacity is crucial for determining whether a battery is considered retired and for evaluating the potential for cascade utilization of these batteries. In the service cycle of retired lithium batteries, there are different degrees of inconsistencies in the residual capacity and internal resistance due to the coupling of various aging factors, so before their cascade utilization, it is necessary to determine the residual capacity value and perform the consistent sorting to ensure that the performance and safety of batteries are improved in the process of cascade utilization.

However, in the two research works on residual capacity estimation and consistency sorting of retired lithium batteries, the research methods in the related fields have the following shortcomings:

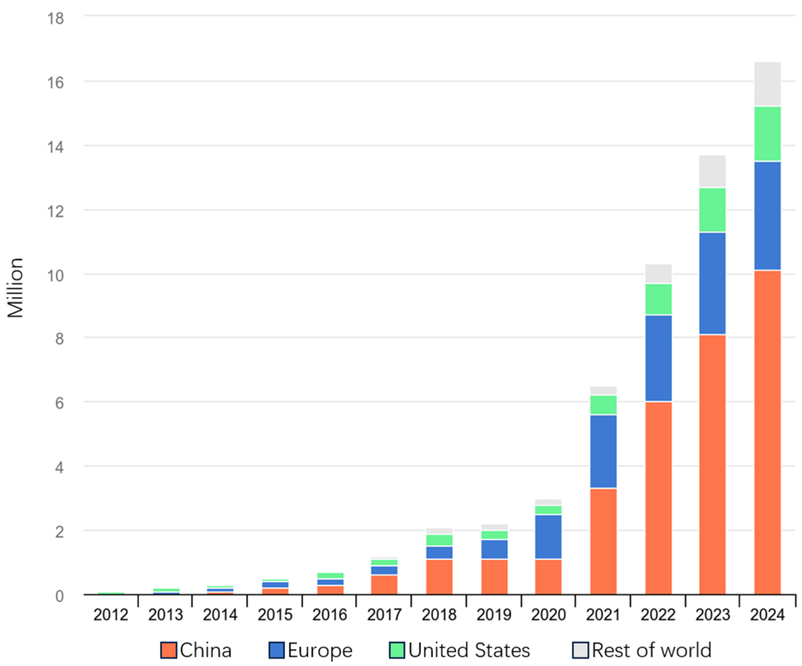


Figure 1. Electric car sales, 2012-2024[3].

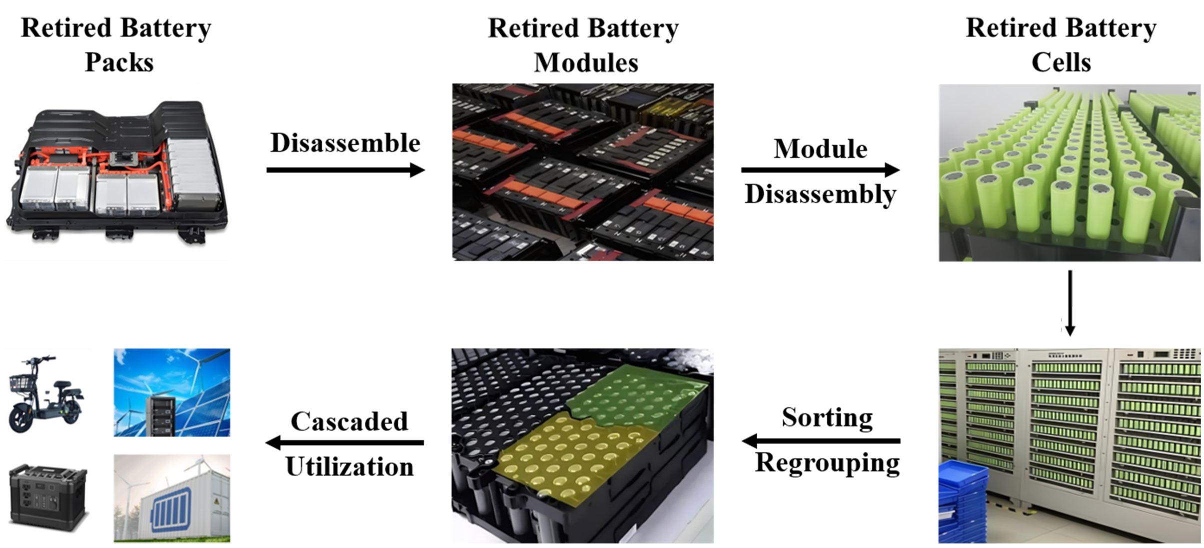


Figure 2. Complete process from retirement to cascaded utilization of power batteries.

• Estimation of the residual capacity of retired batteries: Residual capacity estimation of retired lithium batteries is a necessary task before cascade utilization. However, the time-consuming residual capacity test of large-scale retired batteries has led to a significant increase in the cost of cascade utilization. Therefore, the residual capacity estimation of retired batteries needs to consider their large-scale and aging factor replication to determine their residual capacity values quickly and accurately.

• Consistent sorting of retired batteries: Most of the existing lithium battery sorting methods are aimed at the new factory batteries, without considering the application scenarios of cascade utilization. Meanwhile, some of the current methods require too much cyclic data, and some of them do not consider the specific changes of current or voltage parameters during the charging and discharging process, and lack specific basic theoretical support. Therefore, the sorting methods for retired batteries should be combined with the application scenarios of retired batteries. Characteristic parameters of sorting should be proposed, the number of cycles required for sorting should be reduced, and the dynamic characteristics of batteries should be considered.

To solve the above problems and further improve the accuracy and rapidity of residual capacity estimation and consistency sorting of retired lithium batteries, researchers have been exploring and developing new techniques and methods. At present, the remaining capacity estimation of decommissioned batteries is mainly based on direct and indirect measurement methods[6]. The direct measurement methods mainly include the Coulomb counting (CC) and the open circuit voltage (OCV) techniques. Then, because the direct measurement method requires much time and effort to complete, it is inefficient and obviously cannot meet the task of residual capacity measurement of large-volume retired lithium batteries. In recent years, the indirect measurement method, which is mainly based on the modeling method and data-driven method, has received extensive attention from researchers[7].

In terms of consistency sorting of retired batteries, there are mainly static parameter sorting methods based on parameters such as capacity, cell voltage[8], and internal resistance[9], and dynamic parameter sorting methods based on changes in battery temperature and charge/discharge curves[10].To make the sorting standard reflect the performance information of retired batteries more comprehensively, comprehensive sorting that combines static and dynamic parameters has been rapidly developed in recent years[11].

Most review papers in this field focus on the electrochemical recycling of retired lithium batteries and the recycling of positive and negative electrode materials or revolve around residual capacity estimation and consistency sorting in battery management systems (BMS)[12-16]. Few have summarized the residual capacity estimation and consistency sorting before the cascade utilization phase of retired lithium batteries. This review is dedicated to comprehensively reviewing the residual capacity estimation methods and consistency sorting methods for retired lithium batteries before they are utilized in cascade, examining the latest research advances, and sharing our insights in this direction. This paper aims to address how to combine modern technologies such as big data, data-driven, advanced algorithms, and machine learning with traditional battery capacity estimation and sorting methods to achieve rapid detection and sorting of upcoming large-quantity retired lithium batteries to meet the rapidly expanding demand of the cascading utilization market. The overall roadmap of this paper is shown in Figure 3.

ESTIMATION OF THE RESIDUAL CAPACITY OF RETIRED BATTERIES

Traditionally, the remaining capacity of retired batteries has been estimated mainly by simple charge/discharge cycle testing methods, which are simple and accurate but suffer from low efficiency, high manpower costs, and limited data processing, making it difficult to meet the growing demand for battery recycling and reuse. Therefore, the development of a more efficient and accurate method for estimating the residual capacity of batteries is not only a demand for technological innovation but also a necessary condition for promoting the stepwise utilization of retired batteries. Currently, the methods for estimating the residual capacity of retired batteries are mainly classified into two main categories: direct and indirect estimation methods.

Direct estimation methods

Direct estimation methods include (i) CC; (ii) OCV; and (iii) Electrochemical impedance spectroscopy (EIS).

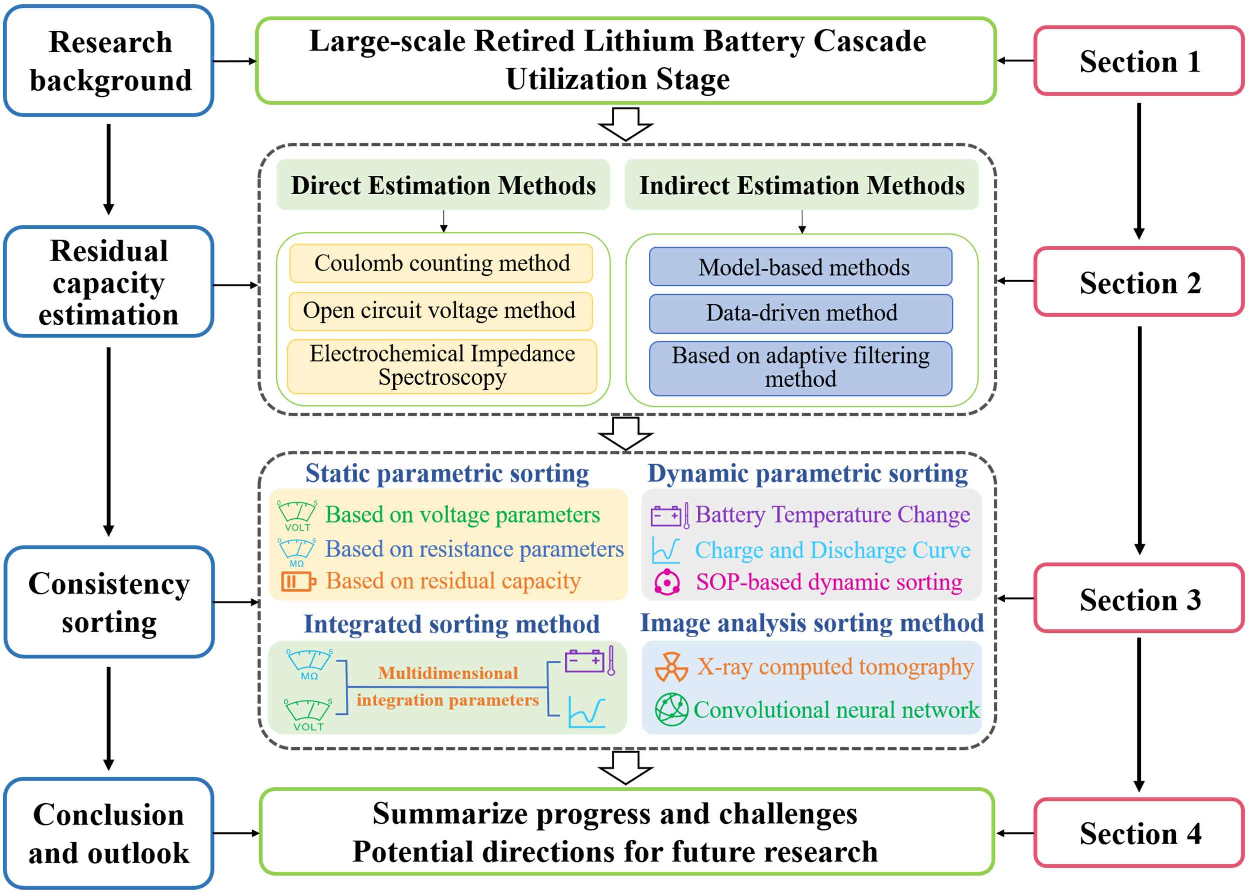


Figure 3. The frame diagram of this review.

CC

The CC method involves fully charging or discharging the battery to estimate the remaining capacity through current integration. The specific implementation method involves connecting a current detection resistor in the battery charging and discharging circuits. During the discharging process, the discharge current is integrated over time to determine the discharging capacity. The remaining capacity can then be calculated by subtracting the discharging capacity from the full charging capacity. However, the disadvantage of this method is that it takes a long time to measure, thus resulting in high time costs. Some scholars have enhanced or improved the traditional CC method to enable the method to measure more accurate values. For example, Lee *et al.* proposed an enhanced coulomb counting method (ECC) that combines the OCV to update the initial value, addressing the initial value error inherent in the CC method[17]. Additionally, the ECC calculates internal resistance, coulombic efficiency, and capacity after each charging/discharging cycle, using these results to improve the accuracy of state of charge (SOC) estimation in subsequent cycles. Zhu *et al.* proposed an improved CC method based on non-destructive charge/discharge differentiation to estimate the SOC of batteries; specifically, it corrects the initial SOC value of the battery using the open-circuit voltage method and corrects the actual capacity of the battery based on the temperature, the discharge rate and the aging[18]. Finally, it uses non-destructive capacity differentiation (dQ/dV) and voltage differentiation (dV/dQ) to correct the cumulative error of the CC method, which effectively corrects the cumulative error of the CC method, and the cumulative error correction flow of the method is illustrated in Figure 4.

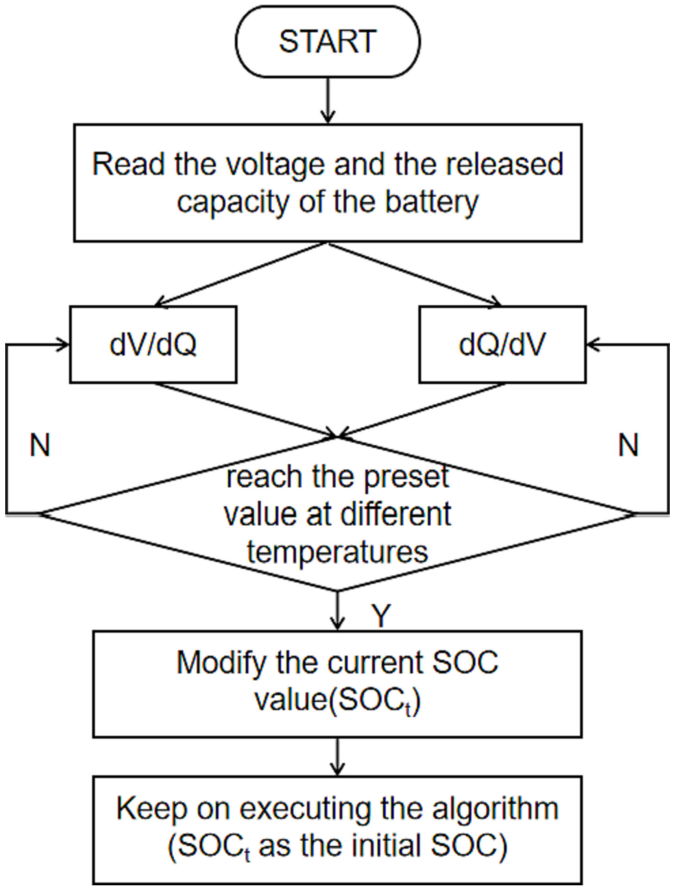


Figure 4. Cumulative error correction flowchart[18].

Based on the OCV method

The OCV-based method is based on the SOC-OCV curve, determining the difference in SOC between any two moments and using the Coulomb change to estimate the current residual capacity of the battery. This method has a high time cost in the need to measure the SOC-OCV curve at low charge/discharge multiples. For lithium iron phosphate batteries, the SOC-OCV curve has a wide flat region, which may lead to a large SOC estimation error and thus affect the accuracy of residual capacity estimation. Braco *et al.* quickly estimated the residual capacity of the battery by measuring the AC and DC resistances of the retired lithium batteries and directly fitting a mathematical model with these data[19]. Duong *et al.* used a simplified model and multiple adaptive forgetting factor recursive least squares (MAFF-RLS) estimation to characterize the OCV-SOC relationship[20], as shown in Figure 5. Ahmeid *et al.* used a simplified equivalent circuit model and incremental capacity (IC) analysis to identify the most informative regions of the discharge profile and then used CC to calculate the residual capacity of the battery module from the partial discharge profile[21].

EIS

EIS, as an important electrochemical analysis technique, can reflect the internal information of a cell over a wide range of frequencies, which is accomplished by measuring the electrochemical impedance at different frequencies. This is done by applying a sinusoidal AC voltage to the battery to be tested and using a frequency response analyzer in combination with a constant potential meter to obtain the electrochemical impedance spectrum, which represents the voltage and current response of the battery versus frequency[22]. Meanwhile, as a non-destructive testing method, EIS ensures the effectiveness and safety of the echelon

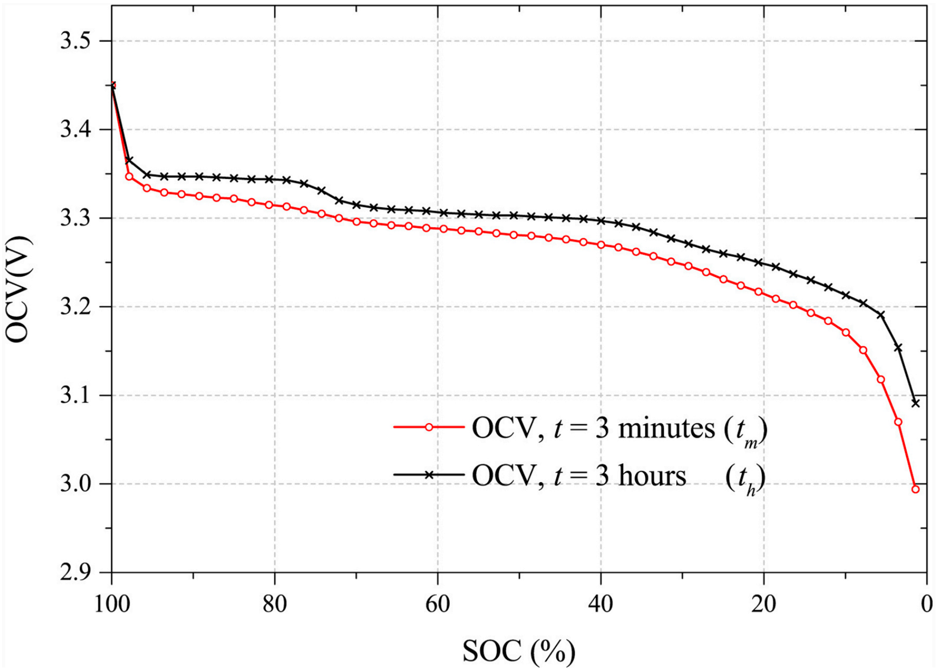


Figure 5. OCV-SOC curves obtained at different relaxation times of 3 min and 3 h in experimental validation[20]. OCV: Open circuit voltage; SOC: state of charge.

utilization of retired batteries to a certain extent. However, the traditional EIS method faces challenges, including a large frequency range and a long time-consuming testing process, and much research progress combines EIS with modeling or data-driven approaches to enhance the accuracy of battery health condition detection. For example, Galeotti *et al.* first proposed to fit the electrochemical impedance spectra with an equivalent circuit model, then reproduced the voltage discharge curve of a lithium battery using the parameters of the equivalent circuit model, and finally assessed the battery health status (SOH) by introducing the relationship between the internal resistance of the battery and the usable capacity[23]. Zhang *et al.* proposed a method for assessing the SOH of retired lithium batteries based on low and medium-frequency electrochemical impedance spectra [simplified equivalent circuit model (SECM)]. The SECM parameters under dynamic conditions were analyzed, showing variation in their values and battery capacity with the number of cycles, as illustrated in Figure 6. Simplified electrochemical impedance spectra parameters of different batteries were then determined to estimate battery SOH[24]. Fan *et al.* used a bidirectional long short-term memory network combined with transfer learning (TL) to learn and predict the capacity of decommissioning lithium batteries of electric vehicles from EIS data. In the case of complex changes in battery status, the method is also extremely effective and is expected to provide a reliable solution for the cascade utilization of large retired batteries[25]. Luo *et al.* established the equivalent circuit model of EIS through experiments on retired lithium iron phosphate power batteries. The parameters of the model are related to the SOC and the SOH of the retired power battery tested, which can realize the rapid detection of the retired power battery in an unknown state[26].

Progress and unresolved issues in direct estimation methods

The progress made in the estimation of the residual capacity of retired lithium batteries by direct measurement methods and the future problems to be solved are as follows:

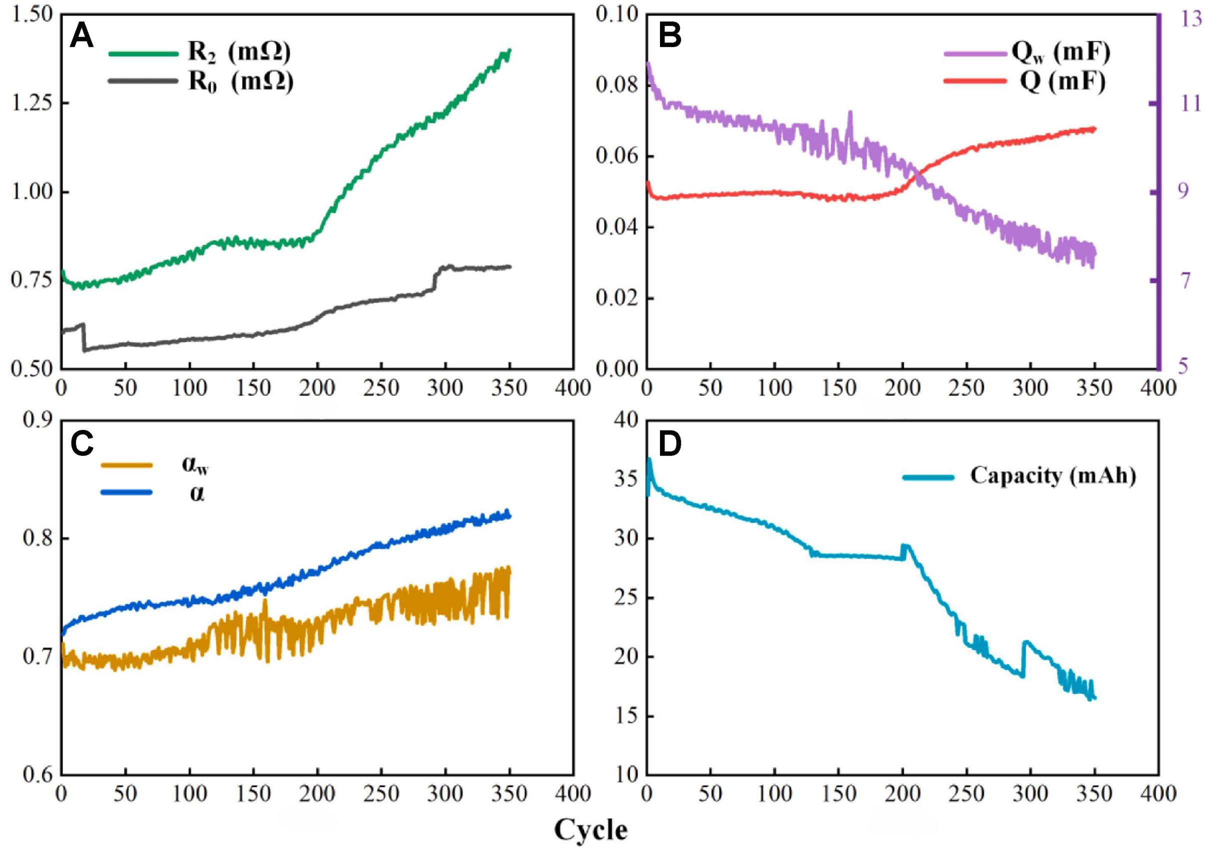


Figure 6. Battery 25C01 SECM parameters and capacity curve. (A) resistance parameter; (B) capacitance parameter; (C) exponential parameter; (D) capacity curve[24]. SECM: Simplified equivalent circuit model.

• CC: With the development of high-precision measurement equipment, the accuracy of current measurement has continuously improved, enhancing the measurement precision of the CC method. In addition, researchers have developed various error compensation algorithms to address the issue of error accumulation caused by self-discharge and polarization effects in the CC method. Some studies have also combined the CC method with other approaches, effectively improving the accuracy and reliability of the residual capacity estimation. However, this method still faces several urgent problems. For example, despite the error compensation algorithm, the error of the CC method will gradually accumulate during the long-term charging and discharging cycles, especially in the case of aging batteries and complex working conditions, and the accumulation of errors may lead to a serious deviation of the capacity estimation results from the real value. In addition, accurate estimation of the initial SOC is crucial for the CC method, but in practical applications, it is difficult to accurately obtain the initial SOC of the battery due to the influence of self-discharge, shelf time and other factors, which leads to the initial error in the capacity estimation.

• Open-circuit voltage method: Researchers have conducted an in-depth study on the modeling of the relationship between open-circuit voltage and SOC, and introduced more complex mathematical models and algorithms, such as the Preisach operator, which can more accurately describe the nonlinear relationship between the two, and especially made significant progress in considering the hysteresis characteristics of the battery. However, the method still faces some limitations; for example, the open-circuit voltage method requires the battery to be rested for a period of time before a stable open-circuit voltage value can be obtained, which may lead to a long measurement time in practical applications. This may hinder the ability to meet real-time requirements and realize large-scale, rapid detection of retired lithium batteries. Additionally, the change of open-circuit voltage is relatively small when the battery's charge state is low, making it difficult to accurately differentiate between different charge states and leading to decreased accuracy of capacity estimation. Therefore, there are some limitations in the application of open-circuit voltage method at low charge states.

• EIS: Currently, scholars in this field have established a more accurate EIS model based on a large amount of experimental data and theoretical analysis for describing the electrochemical processes and electrode interface characteristics inside the battery. Meanwhile, by optimizing the model structure and parameters, the adaptability and prediction ability of the model for various types of batteries with different degrees of aging have been improved. The application of the migration learning technique in EIS has achieved certain results, which reduces the cost of repetitive testing, modeling, and training for specific batteries by migrating the basic model established under laboratory conditions to retired batteries with different operating conditions and types while maintaining the accuracy of capacity estimation, providing new ideas and methods for the rapid detection and evaluation of large-scale decommissioned batteries. However, the unavoidable difficulty is that the measurement of EIS requires specialized impedance analyzers and other equipment, which are expensive and complicated to operate, limiting its wide application in the detection of large-scale retired lithium batteries. Meanwhile, the measurement of EIS requires strict control of the measurement conditions to ensure the accuracy and comparability of the measurement results. However, in practical applications, it is difficult to ensure that the ideal measurement conditions can be met in all cases.

Indirect estimation methods

Indirect estimation methods do not directly measure the SOH of a battery; instead, they estimate it by collecting and analyzing parameter changes within the battery system using models and algorithms. These indirect analysis methods can be broadly categorized into three categories: model-based methods, adaptive filter-based methods, and data-driven methods.

Model-based methods

The model method determines the health state of a battery by constructing different battery models. Among them, the more representative two types of battery models are the electrochemical model and the equivalent circuit model. Zhang *et al.* proposed a method for health estimation of decommissioned batteries based on mid-low frequency EIS. The low- and medium-frequency electrochemical reactance spectra under dynamic conditions were used to identify the simplified electrochemical impedance spectra of different cells for the estimation of battery health[24]. Fan *et al.* used a bidirectional long short-term memory network combined with TL to learn and predict the capacity of decommissioned electric vehicle lithium batteries from EIS data. This method is also extremely effective in the case of complex changes in battery status and is expected to provide a reliable solution for the cascading utilization of large retired batteries[25]. Luo *et al.* established an equivalent circuit model of EIS through experiments on decommissioned lithium iron phosphate power batteries. The parameters of this model are related to the charging state and health state of the decommissioned power battery under test, which can realize the rapid detection of the decommissioned power battery in an unknown state[26].

Adaptive filter-based methods

The method based on an adaptive filter is a combination of a direct estimation method and algorithm, which can realize real-time feedback of data. Common adaptive filter-based methods include Kalman filter (KF)-based methods and recursive least squares (RLS), which are used in the study for SOH estimation. Fahmy *et al.* proposed a method that combines an adaptive odorless KF with CC. As shown in Figure 7, the

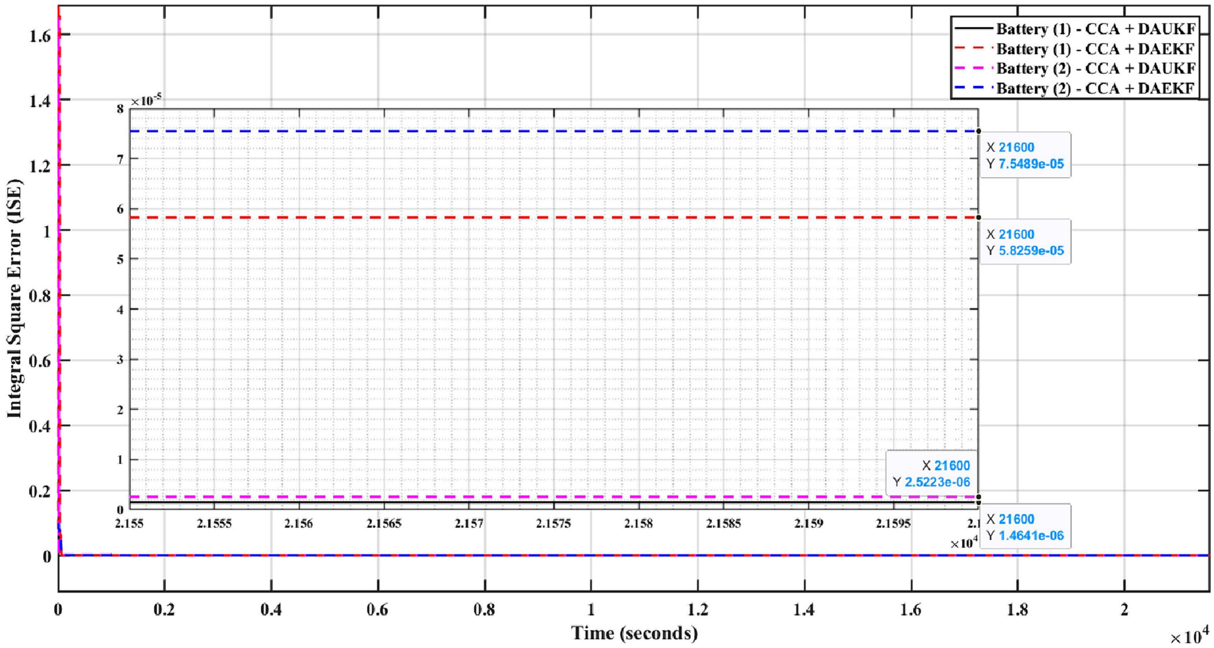


Figure 7. Integral squared error curves of LIBs[27]. LIBs: Lithium ion batteries.

dual adaptive unscented Kalman filter (DAUKF)-Coulomb counting approach (CCA) method results in less error than the AEKF-CCA method in both battery conditions. Through simulation analysis, the error between the results obtained from this method and the measured results is less than 1%[27].

Oji *et al.* proposed a variable forgetting factor recursive least squares (VFFRLS) algorithm to identify the battery model to avoid the effect of current fluctuation. The real value of OCV was obtained by performing OCV experiments on the battery, and the results obtained were compared with the data obtained from the kinetic model, which showed that the VFFRLS algorithm has the highest accuracy and makes the parameters of the SOH model more precise[28].

Data-driven methods

Because of its high precision and high efficiency, data-driven methods have been widely studied and applied in the estimation of the residual capacity of decommissioned batteries. The principle is to extract health indicators from battery data and use artificial neural networks (ANNs), deep learning (DL), TL, and other algorithms to establish a relationship mapping model between health indicators and residual capacity. To quantify the SOH health indicators of soft clustering decommissioned lithium-ion batteries, the method requires a certain amount of past cell history data. Therefore, the model requires a certain amount of prerequisite data to train the model to accurately predict the health state. Camboim *et al.* used a method based on EIS and ANNs to estimate the state of lithium-ion batteries. They input test data into the model to verify the accuracy of the neural network. As can be seen from Figure 8, the estimated battery health value of the neural network is very close to the actual battery health value[29].

In view of the incomplete battery health data caused by random charging and discharging behavior of electric vehicles, Xiong *et al.* used a DL algorithm to pre-process the online data and input the SOH estimation model, as shown in Figure 9[30].

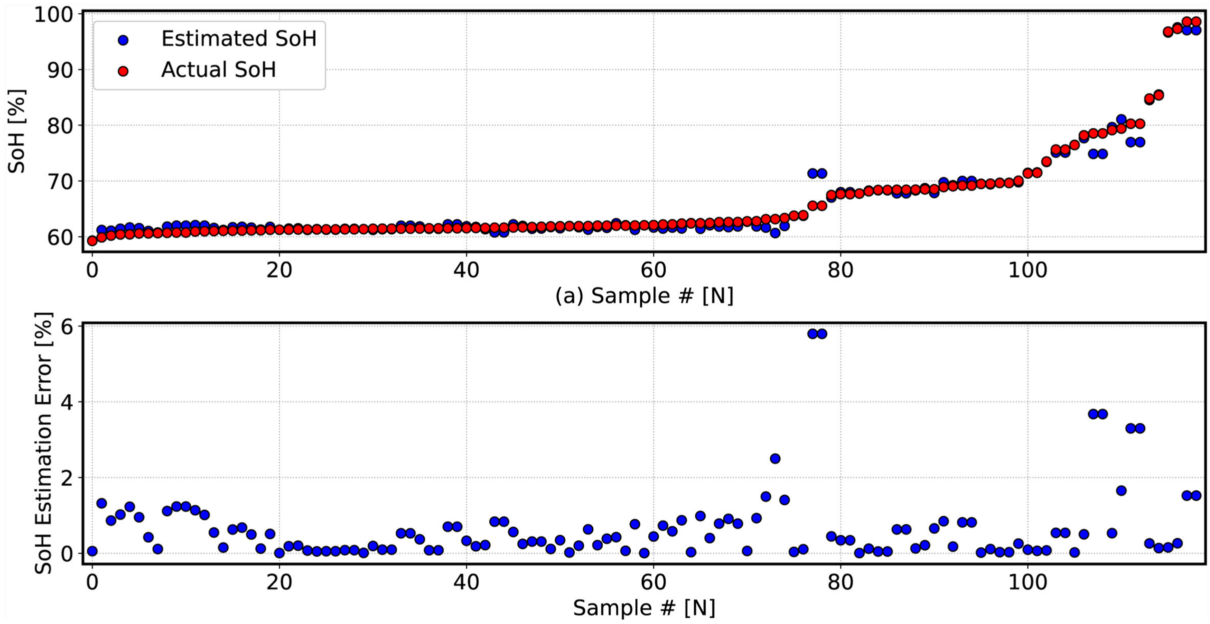


Figure 8. High-capacity LFP sample. (A) Comparison of the SOH estimated by the NN (blue dots) and the actual SOH (dots in red); (B) The error between the SOH calculated by the NN and the actual SOH[29]. LFP: Lithium iron phosphate; SOH: battery health status; NN: neural network.

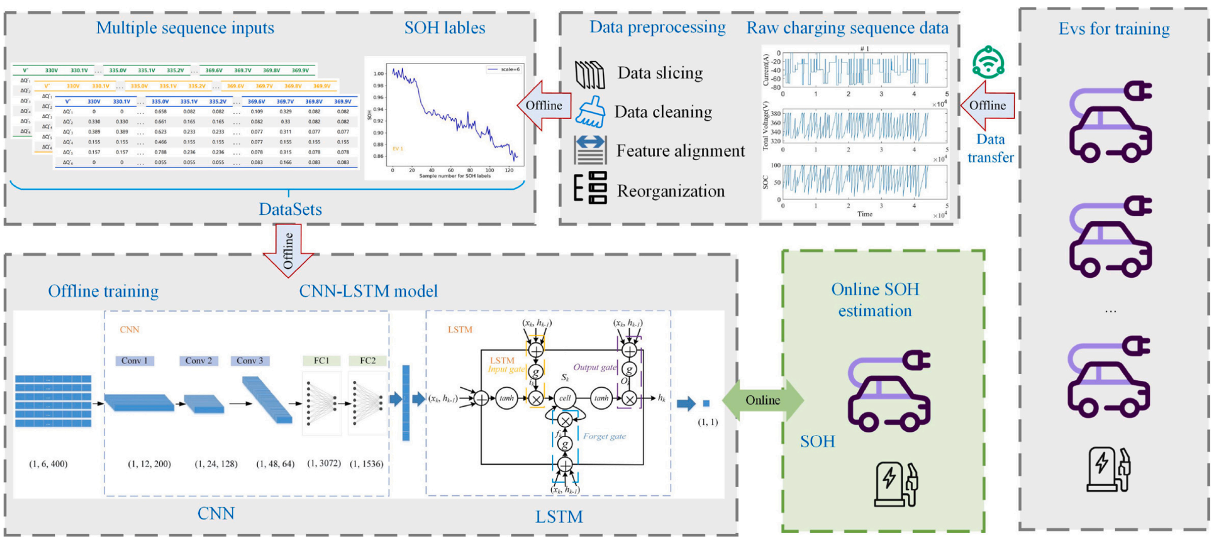


Figure 9. Flowchart of the proposed online SOH estimation method[30]. SOH: Battery health status.

The final results prove that the model is beneficial to improving the accuracy of battery SOH estimation[30]. Deng *et al.* used the early aging data of batteries for degradation pattern recognition and TL. The main ideas for SOH estimation are shown in Figure 10. It can be shown from Figure 11 that TL improves the estimation accuracy of battery capacity under different degradation modes[31].

To meet the need to estimate the remaining capacity of batteries under dynamic conditions, Yang *et al.* proposed a joint adaptive deep TL model[32], which collects data such as voltage, current, temperature, charging state, and accumulated discharge capacity as input characteristics, as shown in Figure 12.

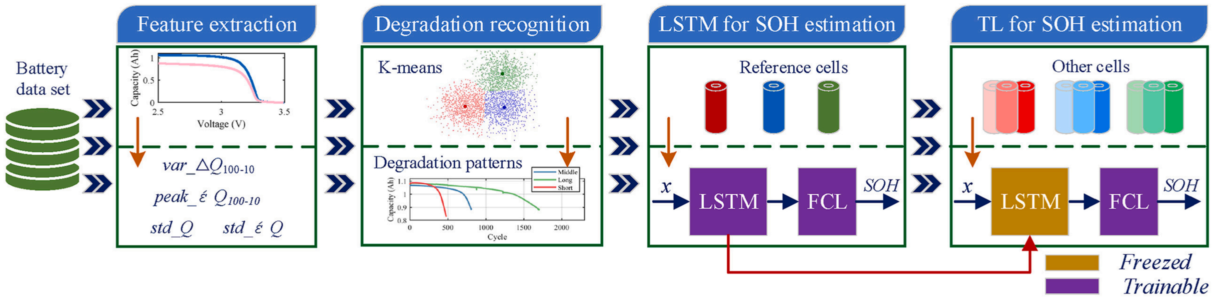


Figure 10. Flowchart of the SOH estimation method[31]. SOH: Battery health status.

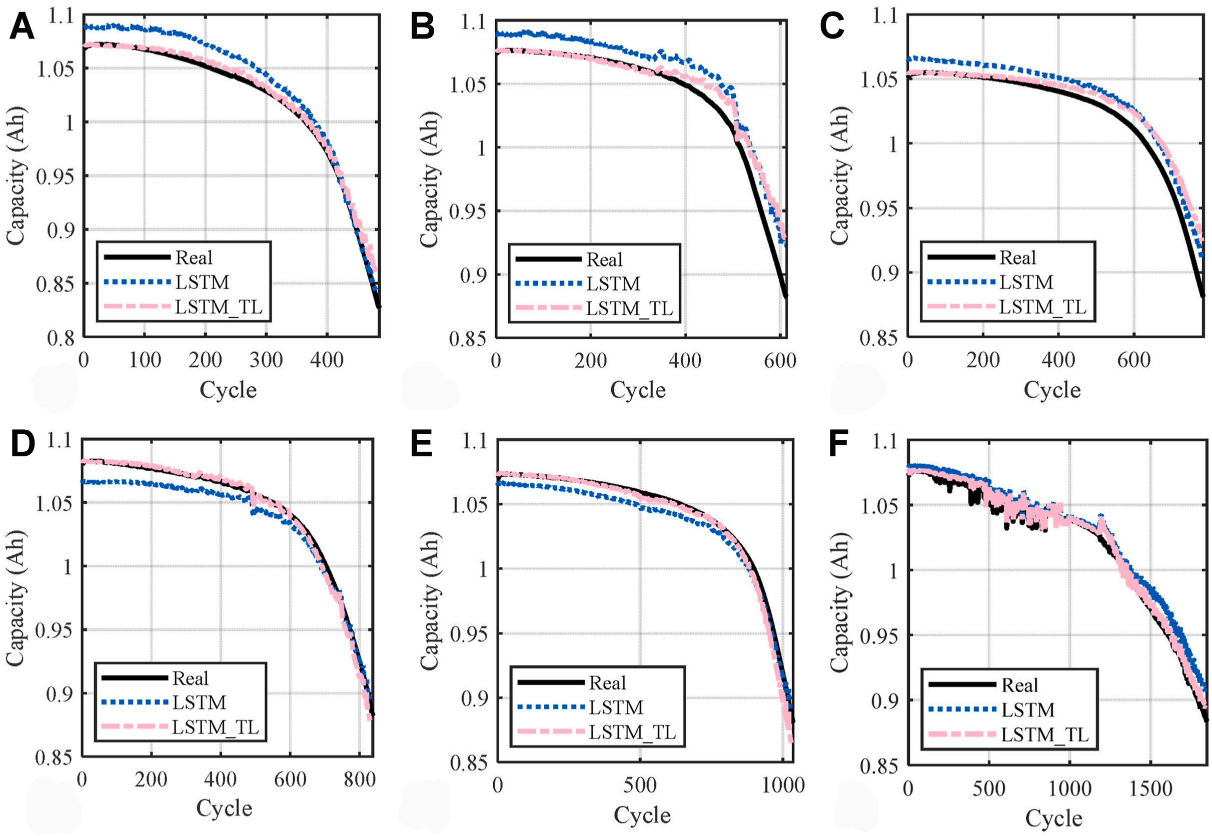


Figure 11. SOH estimation results based on the TL for typical cells. (A) Cell with 4.8C(80%)-4.8C policy; (B) Cell with 7C(40%)-3.6C policy; (C) Cell with 5.6C(36%)-4.3C policy; (D) cell with 6C(40%)-3.6C policy; (E) Cell with 5.3C(54%)-4C policy; (F) Cell with 3.6C(80%)-3.6C policy[31]. SOH: Battery health status; TL: transfer learning.

Experiments show that the SOH value obtained under extreme conditions is also very accurate. However, the model needs to be optimized in terms of parameter processing and model volume[32].

Progress and unresolved issues in indirect estimation methods

In summary, the estimation of the remaining capacity of retired batteries is mainly indirect. Most of these methods are based on data-driven approaches, which have significant advantages in decommissioning battery estimation. Most research is based on lossy charge and discharge modes, and the battery simulation models have complex parameters and limited interpretability. The selection of health indicators lacks the exploration of the internal parameters of the battery, and the machine learning algorithms are mostly single

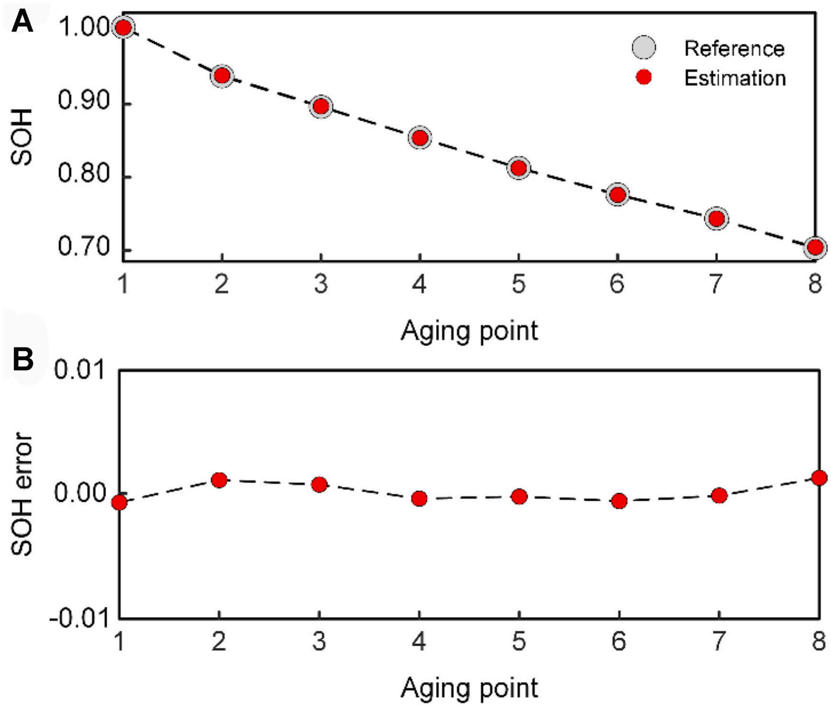


Figure 12. SOH estimation results based on estimated SOC in the simulated experiment. (A) estimated SOH; (B) SOH estimation error[32]. SOH: Battery health status; SOC: state of charge.

traditional algorithms, which limits the generalization ability and overall prediction performance of the prediction model to a certain extent. It is worth noting that the data-driven approach requires a certain amount of historical data on retired batteries to train the model to quantify the health indicators of the health state of retired batteries, to achieve accurate pre-measurement of the health state of batteries[6].

CONSISTENCY SORTING OF RETIRED BATTERIES

Traditionally, the consistency sorting process of retired batteries includes assessing the type of battery, conducting a visual inspection, assessing the voltage and residual capacity, and then manually categorizing and organizing the individual batteries. This method is not only inefficient, but also consumes a lot of human and material resources, and the accuracy and effectiveness of sorting are still insufficient. With the surge in the number of retired batteries and the development of science and technology, the traditional screening method has become outdated, and efficient and accurate sorting methods are being developed and applied. In recent years, many scholars have conducted extensive explorations and research on the consistent sorting of retired batteries. With the development and popularization of machine learning and big data technologies, most of the studies extract key sorting indexes from various battery performance tests (charge and discharge test, pulse voltage test, EIS test, *etc.*) and combine them with machine learning algorithms [K-means, Gaussian mixture model (GMM), support vector machine (SVM), *etc.*], aiming to achieve fast and accurate screening of retired batteries. Currently, in a data-driven context, the sorting methods for retired batteries can be summarized into four types: static parametric sorting, dynamic parameter sorting, comprehensive parameter sorting, and image analysis sorting.

Static parametric sorting

In general, static parametric sorting methods are divided into two types: single-parameter and multi-parameter, and the following section highlights the relevant advances of the two methods and summarizes the problems to be solved in the future.

Single-parameter sorting method

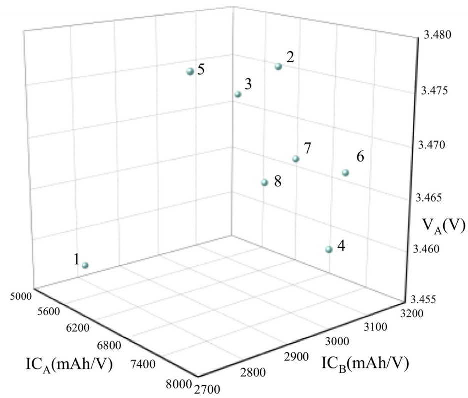
Static sorting of retired batteries focuses on their basic characteristics, relying on fixed and invariant properties such as residual capacity, internal resistance, and voltage. This method can be categorized into single-parameter sorting and multi-parameter sorting according to the number of sorting parameters. In single-parameter sorting, a certain static parameter of the retired batteries is selected as a sorting index. Yang *et al.* analyzed the relationship between battery capacity decay and Coulombic efficiency, monitored the Coulombic efficiency value online using a statistical quality control method, and proposed a model based on Coulombic efficiency to accurately estimate the capacity of the battery to screen batteries that are suitable for secondary use[33]. Li *et al.* investigated five sorting methods for $LiFePO_4$ batteries, including battery capacity detection, battery resistance detection, EIS model detection, battery voltage profile detection, battery dynamic parameter detection, and battery heat generation detection[34]. They focused on the correlation between impedance parameters, surface temperature rise, and internal resistance; however, they did not consider multiple characteristics of the battery for sorting. Chen *et al.* proposed a sorting method based on the capacity-voltage curve deduced from the IC curve, and applied it to 320 retired $LiFePO_4$ batteries, using the peak of the IC curve as a feature for sorting[35]. Figure 13 shows the characteristic points of their curves and the experimental results, demonstrating that a relatively good sorting outcome was achieved. He *et al.* used temperature as the main state index for sorting Li-ion batteries, solving the issue of insufficient response to the internal working state of the battery[36]. They assessed individual batteries in the battery module based on temperature differences. However, despite the speed and simplicity of single-parameter sorting, the method provides incomplete information on retired batteries. In particular, the consistency of battery capacity decay over time cannot be guaranteed, leading to excessive differences among the sorted batteries and ultimately reducing sorting accuracy.

Multi-parameter sorting method

To address this deficiency, multi-parameter sorting has become the main sorting method nowadays. Wei *et al.* extracted four sorting indices - initial residual capacity, ohmic internal resistance, polarization internal resistance, and open-circuit voltage - based on the second-order resistor-capacitor (RC) equivalent circuit model[37]. They combined the entropy weight method with grey correlation analysis to establish a multi-indicator comprehensive performance evaluation system for batteries, which can effectively realize the screening of retired batteries. Garg *et al.* used multiple parameters of retired batteries - residual capacity, voltage, temperature, and internal resistance - as sorting indices[38]. They combined these parameters with a self-organizing map (SOM) neural network to classify and reorganize retired batteries. Liu *et al.* used residual capacity, internal resistance, and open-circuit voltage as classification indices to sort batteries using an analytical hierarchy process and gray correlation analysis and improved the consistency of retired battery sorting by combining density-based clustering and GMM for battery regrouping[39]. Figure 14 shows the clustering and grouping results for the three types of batteries. Wang *et al.* combined two parameters, capacity and resistance, and obtained multiple aging features from the IC analysis curves, the EIS curves, and the current curves during the constant voltage charging to classify retired batteries, avoiding the time-consuming classification caused by obtaining battery capacity[40]. Moreover, the relevant features were input into a machine learning model to assess classification accuracy, and the results shown in Figure 15 indicated that the classification accuracy exceeded 95%.

Liao *et al.* performed comprehensive battery classification and proposed that pulse discharge voltage is an important index for evaluating the consistency of retired batteries[41]. Yin *et al.* used the discharge capacity and temperature rise as the initial sorting features, and used the noise-based application of the density

A



B

Average voltage difference(mV)	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8
B 1	0	22.2	27.2	18.4	31.4	19.3	18.3	14.5
B 2	22.2	0	5.12	12.5	9.8	8.71	9.47	13.9
B 3	27.2	5.12	0	15	7.23	11.2	11.9	16.4
B 4	18.4	12.5	15	0	22.2	4.11	3.35	3.94
B 5	31.4	9.8	7.23	22.2	0	18.4	19.2	23.6
B 6	19.3	8.71	11.2	4.11	18.4	0	1.25	5.58
B 7	18.3	9.47	11.9	3.35	19.2	1.25	0	4.45
B 8	14.5	13.9	16.4	3.94	23.6	5.58	4.45	0

C

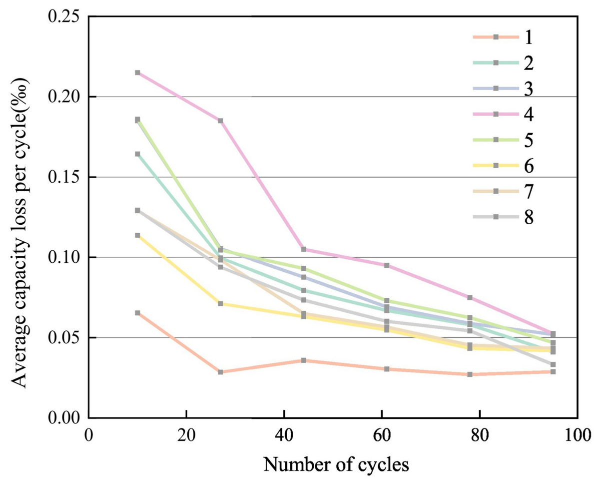


Figure 13. (A) Eight characteristic points of the IC curve of batteries; (B) Average voltage difference matrix of eight batteries; (C) Experimental results of capacity decay[35]. IC: Incremental capacity.

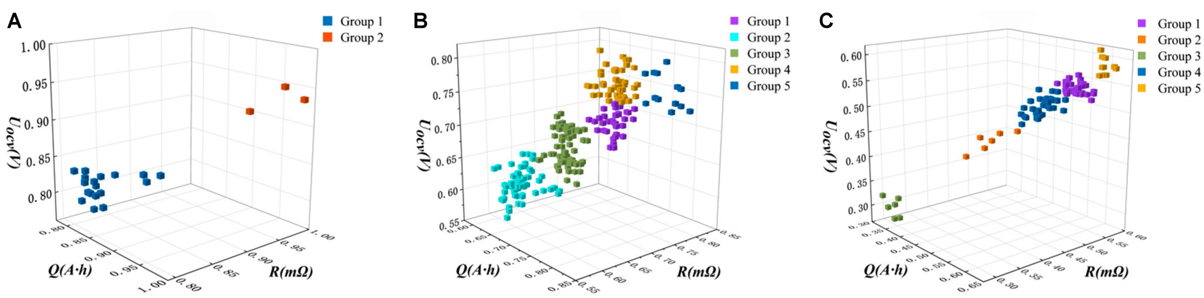


Figure 14. Results of clustering and grouping of three types of batteries. (A) Category A batteries; (B) Category B batteries; (C) Category C batteries[39].

spatial clustering (DBSCAN) algorithm for the initial sorting, to eliminate the abnormal batteries and obtain the possible number of clusters K, to pave the way for the second stage of the battery sorting through the K-means clustering algorithm, and the sorting results have a significant comprehensive consistency[11]. Qiang *et al.* proposed a multi-class kernel function SVM-based screening method for retired lithium-ion batteries, which collects the capacity, voltage, and DC resistance as the main parameters, and uses the capacity/voltage second-order conductivity curve to quickly extract the capacity characteristics as the input to the SVM to

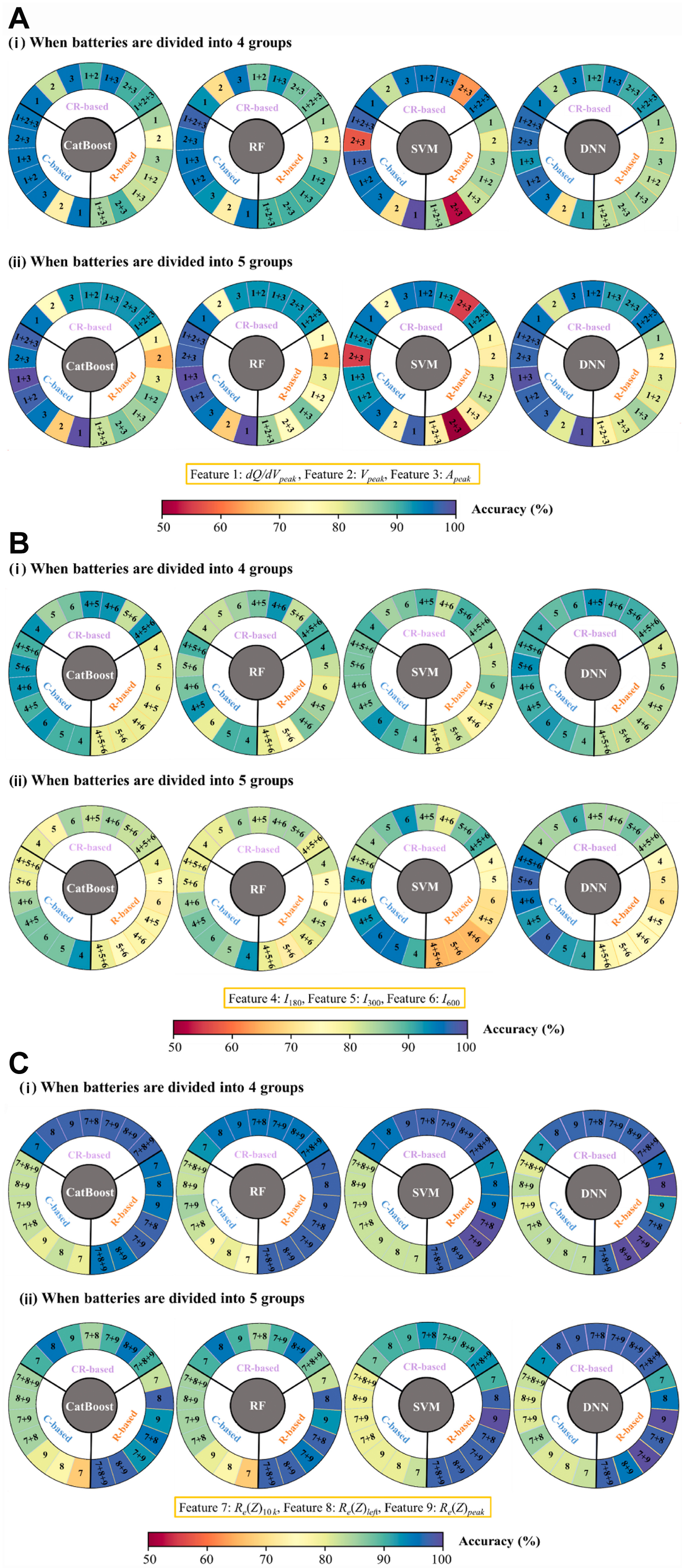

A
(i) When batteries are divided into 4 groups
(ii) When batteries are divided into 5 groups
CatBoost
RF
SVM
DNN
CR-based
C-based
R-based
Feature 1: dQ/dV_{peak}, Feature 2: V_{peak}, Feature 3: A_{peak}
Accuracy (%)
50 60 70 80 90 100
B
(i) When batteries are divided into 4 groups
(ii) When batteries are divided into 5 groups
Feature 4: I_{180}, Feature 5: I_{300}, Feature 6: I_{600}
Accuracy (%)
50 60 70 80 90 100
C
(i) When batteries are divided into 4 groups
(ii) When batteries are divided into 5 groups
Feature 7: $R_e(Z)_{10k}$, Feature 8: $R_e(Z)_{left}$, Feature 9: $R_e(Z)_{peak}$
Accuracy (%)
50 60 70 80 90 100

Figure 15. Accuracy analysis of the classification using various combinations of the three features (1, 2, 3) taken from the ICA curves (A), the CV curve (B) and the EIS curve (C) the three classification criteria, and the four algorithms when the batteries are classified into (i) 4 and (ii) 5 groups[40]. ICA: Incremental capacity analysis; CV: constant-voltage; EIS: electrochemical impedance spectroscopy.

categorize retired batteries, with an accuracy rate of 97.0%[42].

Zhao *et al.* proposed a method for evaluating the availability of retired batteries, enabling the sorting and evaluation of Cascade utilization of retired batteries by relying solely on simple parameters such as internal resistance, residual capacity, lifespan, and diaphragm performance[43]. The measurement is simple and efficient, and the evaluation results are scientific and reliable. This method can greatly improve the efficiency of classifying the availability of retired lithium power batteries. In conclusion, the multi-parameter sorting method can evaluate the battery performance more reasonably and objectively. However, it should be emphasized that when multiple factors are considered, different weights should be assigned according to the importance of each factor.

Progress and unresolved issues in static parametric sorting

As an earlier sorting method, the single-parameter sorting method fails to reflect the consistency of the battery's internal characteristics and ignores the interrelationships among the parameters, which leads to extremely limited adaptability of the sorting results. The multi-parameter sorting method solves the problem of one-sided sorting results to a certain extent; however, it still faces challenges in handling large volumes of experimental data. The important index of retired batteries in the secondary utilization is economic feasibility and the comprehensive consideration of multiple parameters needed to determine the weight of different parameters, which leads to the complexity of the sorting process, which in turn increases the cost of battery secondary utilization. Therefore, low sorting efficiency is the main problem faced by the current static parameter sorting method.

Dynamic parameter sorting

Retired batteries exhibit a range of changing parameters during charging and discharging, such as temperature changes and charge/discharge curves, which are known as the dynamic characteristics of the battery. The method of classifying batteries based on these characteristics is known as dynamic characterization. The advantage of this approach is that it ensures that the classified battery packs have highly consistent dynamic characteristics and reveals key characteristics of the cells, including internal resistance, capacity, and voltage.

Dynamic characteristics refer to the performance of the battery under dynamic and complex operating conditions. It mainly includes dynamic battery characteristics such as voltage curve, current-voltage (IC) curve, and temperature change curve.

Sorting method based on battery temperature change

The use of temperature as a core indicator for battery classification can effectively address the shortcomings of existing methods in monitoring the internal working state of batteries. By continuously monitoring the state of individual cells in a battery module, it is possible to assess how stable the entire system is after performing a large-capacity battery combination. During the charging and discharging tests, the temperature changes of the batteries are precisely measured and their rates of temperature rise and change are compared, thus revealing the intrinsic performance of the batteries under dynamic operating conditions.

Zhao *et al.* proposed an online surface temperature prediction and anomalous temperature diagnosis method based on a hybrid neural network and fault threshold optimization algorithm[44]. Li *et al.* investigated the electrochemical-thermal behavior of decommissioned power lithium-ion batteries under high temperatures and overcharge or over-discharge cycles[45]. Gu *et al.* proposed a rapid screening method for decommissioned batteries based on the prediction of IC curves of lithium-ion batteries through techniques such as SVMs[46]. Ling *et al.* monitored the internal lithium-ion battery *in situ* through a high throughput selection method temperature[47], *etc.*

To differentiate between battery performance differences and reject substandard products, He *et al.* proposed a lithium battery classification method based on temperature analysis[36], through the data of temperature change with time during the charging and discharging process of multiple cells, and drawing the temperature-time curve, as shown in Figure 16, which in turn provides visualization support for the consistency sorting work of the cells.

By detecting and analyzing temperature changes, the problem of inadequate response to the internal operating conditions of the battery can be solved. Dynamic temperature changes in batteries can be detected by charge/discharge tests. Comparing the temperature rise and warming rate of the battery can reflect the internal performance of the battery during dynamic operation. This method can be used to identify the inconsistency of batteries, screen out unqualified batteries, and in turn facilitate the further sorting and restructuring of retired lithium batteries in the cascade utilization phase.

Sorting method based on charge-discharge curves

In traditional steady-state charge/discharge tests (e.g., constant-current-voltage, constant-current charging, and constant-voltage charging), battery performance evaluation and classification are usually based on the charge/discharge curve. Methods based on battery charge/discharge curves can provide a more in-depth and comprehensive understanding of battery performance, but data analysis and processing are also more complex. Liu *et al.* proposed an enhanced approach for decommissioned battery sorting that utilizes multidimensional features extracted from voltage profiles and a multi-clustering algorithm based on these features for scoring fusion mechanisms for different scenarios[48]. Xu *et al.* extracted seven feature indicators such as charging and discharging capacity, energy, and ampere-time efficiency from the charging and discharging curves, and applied principal component analysis (PCA) to downsize to three classification indicators, combined with traversal optimization clustering algorithms to achieve consistency clustering of retired batteries[49]. Liu *et al.* realized the accurate sorting of retired batteries by extracting five key features of partial charging segments and IC curves as sorting criteria, combined with SOM and subtractive clustering algorithms[50]. Tian *et al.* extracted the charging voltage curves as dynamic features and evaluated the inconsistent state using the RLS method combined with the DBSCAN[51]. Liu employed the peak of the IC curve as a feature to ensure the long-term consistency of the recombinant batteries in terms of capacity degradation[50]. Wei *et al.* trained an SVM model using the peak coordinates of the IC curve[37]. The results showed a decrease in the mean value of the current standard deviation by about 14 times.

In addition, Pan *et al.* used a combination of static and dynamic features to assess the consistency sorting of retired batteries and proposed a multi-stage deep sorting strategy based on static and dynamic feature clustering[52], in which voltage curves are also considered as a sorting feature to improve the accuracy and safety of battery sorting, and the overall flowchart of the method is shown in Figure 17.

Progress and unresolved issues in dynamic parametric sorting

At present, the dynamic parameters of the retired lithium battery sorting method have made significant

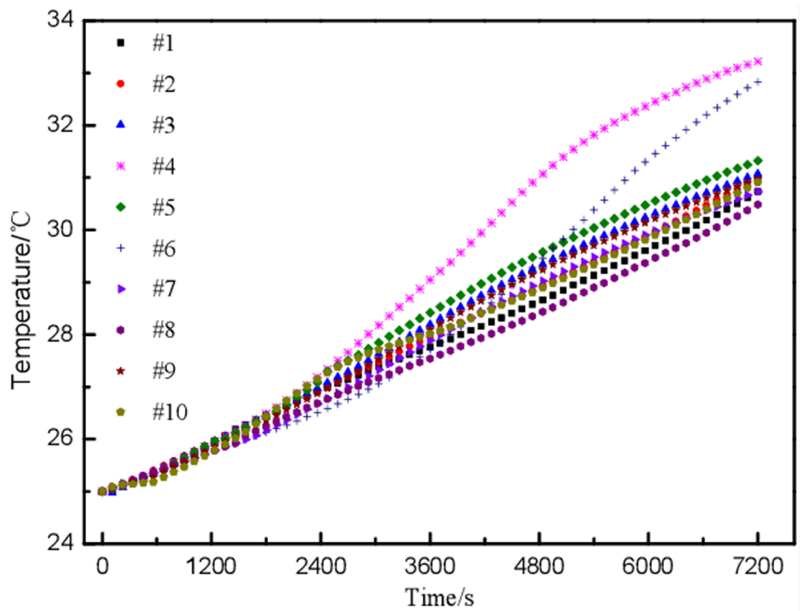


Figure 16. Temperature trends during charging and operation of different cells[36].

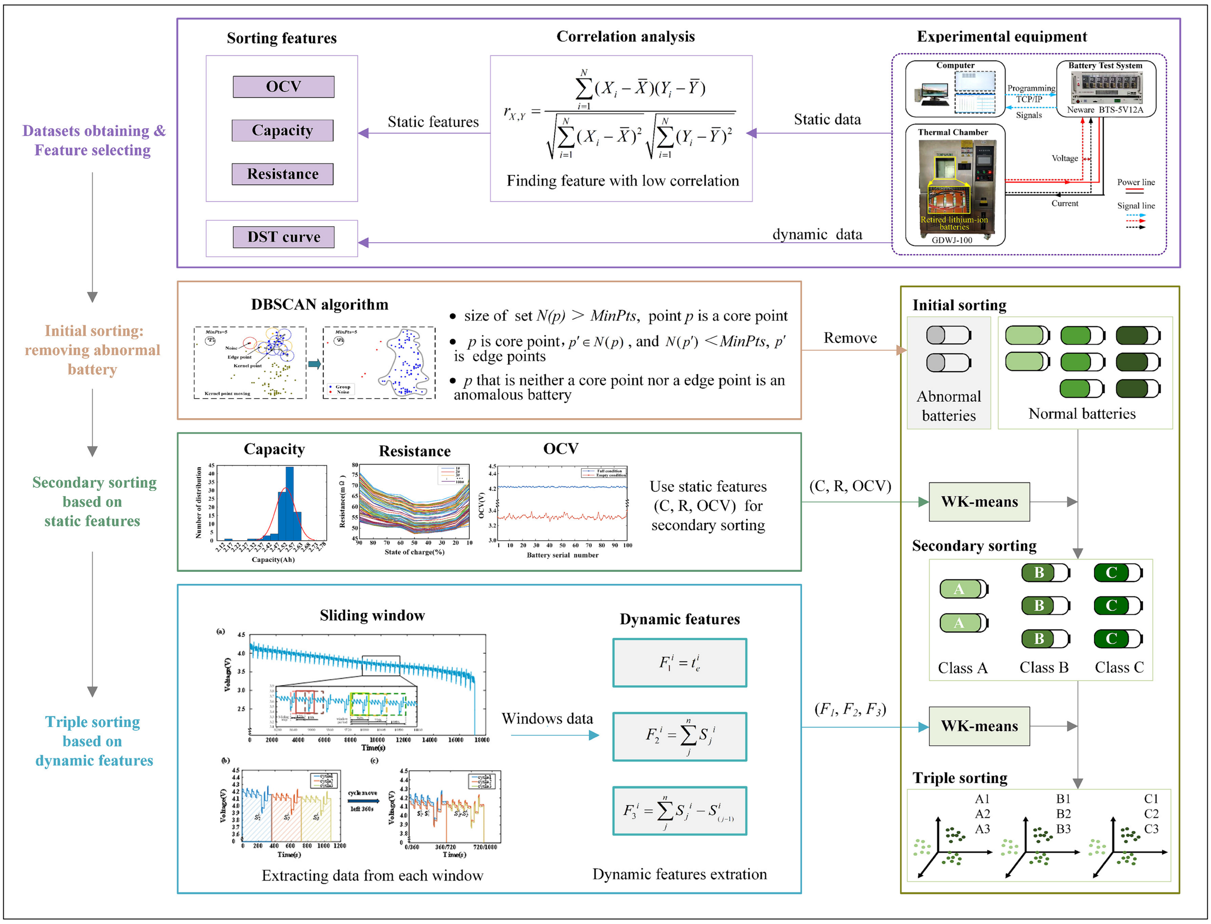


Figure 17. The framework of multi-stage sorting strategy[52].

progress. At the level of theoretical research, researchers have conducted an in-depth analysis of the dynamic parameters of the battery, such as voltage and current change rules during charging and discharging, as well as the dynamic characteristics of the internal resistance, *etc.*, and established a complete mathematical model to simulate the evolution of battery performance with the dynamic parameters, which provides a theoretical basis for the sorting. In terms of technical practice, dynamic parameter-based sorting equipment is constantly optimized and upgraded, with higher detection accuracy and faster sorting speed, which can achieve efficient screening of a large number of retired lithium batteries. Some advanced sorting systems also incorporate intelligent algorithms, which can automatically determine the consistency sorting and SOH of the battery based on dynamic parameters, improving the accuracy and reliability of sorting. Some enterprises have applied the sorting method in actual production, significantly improving the efficiency and quality of retired lithium battery cascade utilization.

However, this method still has some unsolved problems. First, the accurate measurement of dynamic parameters faces challenges. Batteries are affected by various complex factors during actual operation, such as ambient temperature, charging and discharging multiplicity, *etc.*, which will lead to fluctuations in dynamic parameters and affect the accuracy and stability of the measurement. Secondly, there are differences in the dynamic parameter characteristics of different types and batches of retired lithium batteries, and it is difficult to establish a unified sorting standard, which limits the generality and consistency of sorting results. In addition, the current dynamic parameter sorting method has a high cost, whether it is the purchase and maintenance of testing equipment, or the computational resources required for data processing, have increased the cost of the technology, which to a certain extent restricts the large-scale popularization and application of the method.

Comprehensive parameter sorting and image analysis sorting methods

Comprehensive parameter sorting

Comprehensive parameter sorting is conducted using both static and dynamic parameters as sorting indicators for comprehensive selection. This method provides more comprehensive battery performance information by integrating the basic attributes and dynamic performance indicators of the battery, which helps achieve more accurate consistency sorting, enabling targeted selection of suitable reuse or recycling strategies. However, the downside of comprehensive parameter sorting is that it requires more complex measurement equipment and data analysis tools. Lyu *et al.* used a hybrid test cycle, genetic algorithm identification of electrochemical model parameters, and PCA dimensionality reduction to extract key sorting indicators, and finally combined semi-parametric clustering methods to efficiently and accurately screen and classify retired batteries[53]. Li *et al.* used remaining capacity, internal resistance, and remaining service life as sorting indicators, and adopted an equal number support vector clustering strategy to achieve consistency sorting and equal quantity recombination of retired batteries[54]. Jiang *et al.* extracted various sorting indicators, including remaining capacity, internal resistance, and IC curve aging indicators, and combined fuzzy clustering algorithms to classify and group retired batteries for two typical application scenarios[55], as shown in Figure 18. Ran *et al.* used remaining capacity and pulse voltage at SOC 5% as sorting indicators, and combined K-means clustering algorithm for rapid sorting of retired batteries[56]. Liao *et al.* used remaining capacity, pulse discharge voltage, charging transfer impedance, and lithium-ion diffusion coefficient as sorting indicators to achieve comprehensive screening based on different battery performance parameters[41]. Pan *et al.* conducted sorting through the Pearson correlation coefficient, and then secondary sorting using the WK means clustering algorithm. Finally, the sliding window method was adopted to extract the time-squared dynamic characteristics from the dynamic stress test data, and the clustering algorithm was used to conduct further precise sub-classification of retired batteries[52]. Yin *et al.* took the discharge capacity and temperature rise as the initial sorting indicators, adopted the DBSCAN algorithm for preliminary sorting, removed abnormal batteries, and obtained the possible number of

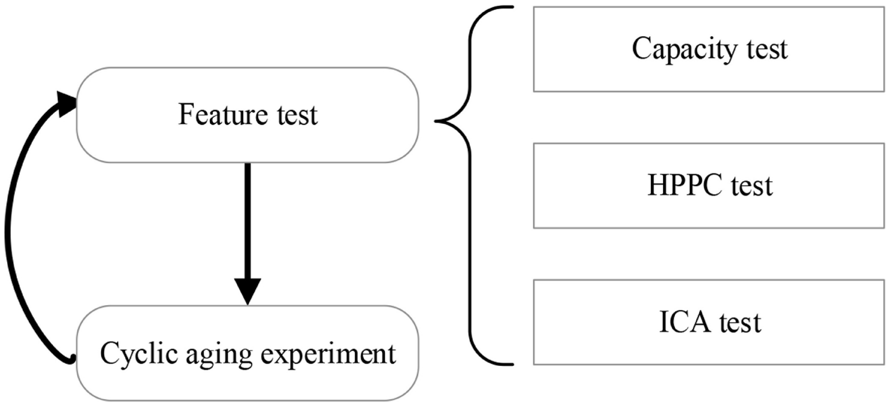


Figure 18. Flow chart of battery cyclic aging and feature tests[55].

clusters K, thus leading to the reference range of the initial values of the K-means algorithm. They also used the dynamic characteristics extracted from the voltage curve by the t-distributed stochastic neighbor embedding (t-SNE) algorithm as the input and obtained the category labels of retired batteries through clustering calculations[11].

Image analysis sorting

Image analysis sorting of retired batteries, as a novel screening method, marks a significant advancement of non-invasive technology in battery assessment and classification. Compared to traditional physical detection methods, this method allows for understanding the internal conditions of the battery without destroying its structure, thus showing great application potential in the assessment and classification of retired batteries. However, this method also faces challenges in terms of cost, data processing, and equipment accessibility. Ran *et al.* used X-ray computed tomography technology, combined with the structural similarity index algorithm, for non-destructive consistency sorting of retired batteries. By analyzing 2,000 CT images, it was found that the CT score is closely related to the battery's internal resistance and remaining capacity, thus achieving an accurate classification of battery SOH[57]. Lin *et al.* used dimensionality reduction technology to process charging voltage sequence data, encoded voltage data into Gramian angular difference fields through inner product operations, and finally, combined ConvNeXt convolutional network to achieve effective classification of retired batteries[58], as shown in Figure 19.

Progress and unsolved problems of comprehensive parameter sorting and image analysis sorting

At present, the research mainly focuses on the comprehensive sorting of dynamic and static parameters. This type of method features good sorting consistency and high precision. However, it requires more complex measuring equipment and data analysis tools compared to single sorting methods. Moreover, the processing algorithms used are relatively simple. The sorting method based on the image analysis of retired batteries is a novel screening approach. It breaks away from the inherent patterns of the previous methods and holds great promise for development. Nevertheless, this method also faces challenges in terms of cost, data processing, and equipment accessibility.

Selection of sorting methods for retired lithium batteries

Consistency sorting of retired lithium batteries aims to sort out batteries with similar performance to improve the overall performance and reliability of the battery pack. Selecting the most appropriate method to optimize the retired battery sorting process requires a combination of factors:

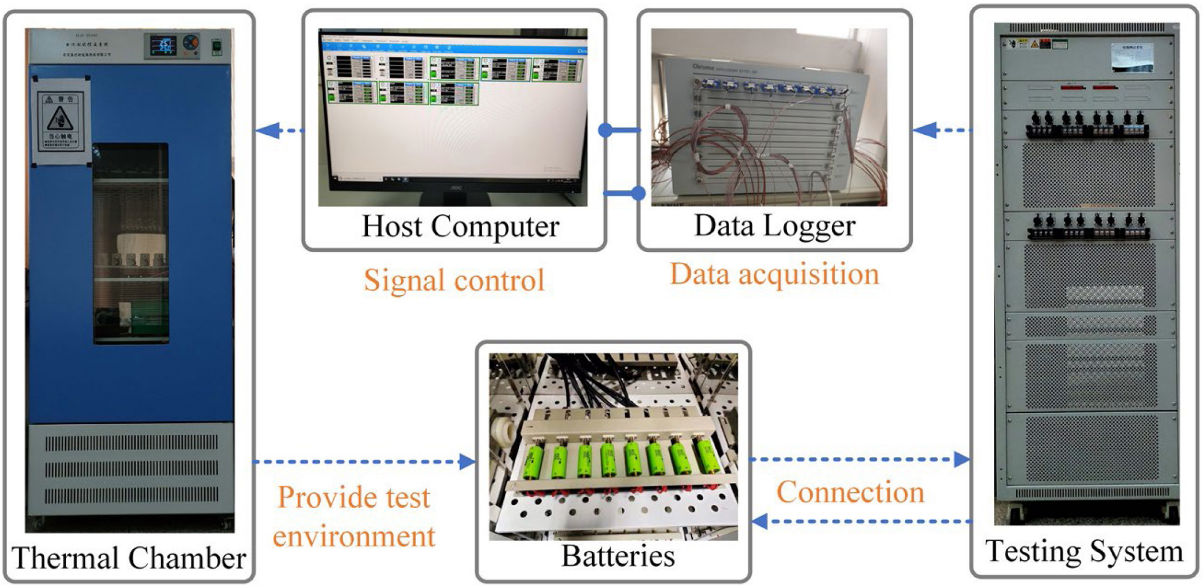


Figure 19. Battery cycle test bench[58].

• Sorting purpose and application scenarios: It is important to clarify the purpose of the sorted batteries. If the batteries are intended for cascade utilization, such as building energy storage systems, there are high requirements for capacity and charge/discharge performance consistency. In this case, an accurate measurement of these parameters is essential. Conversely, if the batteries are to be recycled, the focus shifts to the rapid differentiation of different types of batteries, allowing for the selection of relatively simple and fast sorting methods, such as appearance detection and voltage initial measurement.

• Battery information and data: It is essential to fully understand the historical use of battery data, including the number of charging and discharging cycles, working environment, *etc*., to help choose the appropriate method. For batteries with complete data records, model-based sorting methods can be used to analyze the trend of battery performance changes based on historical data. In cases where historical data is lacking, real-time detection methods should be employed, such as direct measurement of internal resistance, capacity and other battery parameters.

• Sorting cost and efficiency: The cost associated with sorting methods includes equipment purchase, operation and maintenance, and labor expenses. For large-scale sorting of retired batteries, it is necessary to select low-cost, high-efficiency methods while ensuring sorting accuracy. For example, the sorting method based on internal resistance and voltage detection features relatively simple equipment and fast detection speeds, making it suitable for large-scale sorting. In contrast, the method based on EIS offers high precision but requires expensive equipment and has a long detection time, making it more appropriate for small batch sorting where precision is critical.

• Sorting accuracy requirements: Different applications have varying requirements for battery consistency sorting accuracy. High-end energy storage applications demand a high degree of consistency in battery performance, and require the use of high-precision sorting methods. These methods often involve a combination of various parameter measurements and comprehensive data analysis. In contrast, applications with lower consistency requirements can be adequately served by simpler sorting techniques, such as voltage sorting or internal resistance sorting.

Additionally, this paper summarizes the applicable conditions and advantages and disadvantages of each sorting method, as shown in Table 1.

CONCLUSION AND OUTLOOK

The rapid expansion of the electric vehicle market is expected to result in a large number of retired lithium-ion batteries in the future; therefore, finding safe and environmentally friendly disposal methods for these batteries is an urgent challenge. Cascade utilization of retired batteries is considered one of the most promising disposal methods. However, to maximize the residual value of these batteries before cascade utilization, it is necessary to estimate their residual capacity and perform consistency sorting. This paper primarily introduces the development status of residual capacity estimation and consistency sorting of retired lithium batteries. By analyzing and comparing different residual capacity estimation methods and consistency sorting strategies, the following conclusions can be drawn:

(1) This paper provides a comprehensive overview of various methods for estimating the residual capacity of retired batteries, including direct measurement techniques based on open-circuit voltage and CC. The open-circuit voltage method is based on Kirchhoff's law and is simple and easy to implement with high accuracy. It can be directly applied in electric vehicle circuits; however, this method requires the battery to be at rest for a while to obtain a stable measurement, making it unsuitable for online estimation. The CC method is advantageous because it is unaffected by voltage measurement distortions and offers higher accuracy and reliability. However, the main problem of this method is that the error of its current sensor accumulates over time, resulting in increasingly larger cumulative errors.

This paper also introduces the modeling method based on electrochemical and equivalent circuits, and the data-driven method based on various machine learning algorithms such as neural networks and SVMs. EIS can reflect the internal information of batteries in a wide range of frequencies; however, the traditional EIS test relies on expensive and specialized precision instruments and is mostly performed in a laboratory environment, which limits its application in large-scale retired battery testing. In recent years, to extend the practical application of EIS, researchers have proposed computational methods utilizing time-domain signal processing techniques[59], which makes the application of EIS to large-scale retired batteries possible. Residual capacity estimation based on the equivalent circuit model is applicable to different types of batteries. However, variations in working conditions or external environments can lead to degraded SOC estimation accuracy due to distortions in the model parameters.

However, both the direct estimation method and the estimation method based on chemical and circuit models struggle to meet the demands for rapid detection of large-volume retired batteries, and their detection accuracy is often unsatisfactory. With the rapid development of artificial intelligence nowadays, residual capacity estimation methods based on data-driven models are widely used[60]. Still, to satisfy the fast and accurate estimation of the residual capacity of large-volume retired batteries, it is necessary to strike a balance between the complexity and accuracy of the models. In addition, most of the current data-driven residual capacity-based estimations are trained and tested using the same type of batteries, and these trained models tend to perform poorly when applied to other types of batteries. Therefore, further research is needed to improve the generalization ability of the data-driven method when predicting different batteries[61]. To address this problem, researchers have proposed using TL techniques to predict the remaining capacity of different types of batteries[62,63], and TL-based methods can transfer learned features from one model to another without being limited by data distribution or labeling[64]. Although preliminary progress has been made in the estimation of the residual capacity of retired lithium batteries based on TL, it needs to be applied to real industrial processes in the future, which requires the establishment of a unified

Table 1. Applicable scenarios and advantages and disadvantages of various sorting methods

Categorization		Applicable scenarios	Advantages	Disadvantages
Static parametric sorting	Single-parameter sorting	● Batteries in small quantities and batches	● Fast sorting speed ● Easy to operate	● One-sided sorting results ● Ignoring parameter correlation
	Multi-parameter sorting	● Batteries with a long remaining life	● Good sorting effect ● Reasonable and objective results	● Complex sorting process ● High cost
Dynamic parametric sorting	Indirect sorting by battery temperature	● Batteries with a discharge capacity of less than 80%	● Fast ● Efficient ● Practical	● Limited scope
	Charge-discharge curve sorting method	● It can be used for abnormally aged batteries	● Good dynamic consistency ● High sorting accuracy	● The process is complex ● Take a long time
Comprehensive parametric sorting		● A large quantity of batteries	● Higher consistency ● Greater precision	● More complex measurement equipment and data analysis tools are required
Image analysis sorting		● A small quantity of batteries	● Without damaging the internal structure of the battery	● High cost

TL framework capable of continuous self-updating to adapt to the complex and changing working conditions in the practical applications in future work.

In summary of the research progress discussed above, this paper proposes a promising direction: using big data to collect historical operation data of retired lithium batteries and integrating the model-based approach with the data-driven approach. This integration aims to combine their respective advantages to solve the problems of low adaptability of the model-based approach, high computational costs, and poor interpretability of data-driven models. The model constructed through this integration method can also use intelligent optimization algorithms or other techniques to fine-tune its parameters, thereby enhancing the integration effect and overall performance of the model. For example, Yayan *et al.* proposed a new approach to predict the SOH of lithium-ion batteries based on stacked BiLSTM deep neural networks[65], which combines an LSTM network with an Elman neural network, where the LSTM is responsible for capturing the long-term dependencies in the SOH sequences while the Elman neural network deals with the short-term fluctuations, and utilizes the advantages of the two neural networks to provide accurate and efficient estimation of battery health. This hybrid model exhibits higher accuracy in predicting the remaining capacity of lithium batteries.

In addition, big data technology plays an important role in the estimation of the remaining capacity of retired lithium batteries by collecting exhaustive data from various types of sensors within the battery pack during the full cycle of the battery service, and effectively and efficiently mining the variable state and feature extraction of the battery's historical operating data or offline test data, and utilizing these features as inputs to the data-driven model to establish a state assessment model, which will provide strong technical support for the battery state assessment and life prediction.

(2) This paper also systematically reviews four kinds of consistency sorting methods for retired batteries, including the direct sorting method based on static parameters of the battery, the indirect sorting method based on dynamic parameters such as battery temperature, charging and discharging curves, the comprehensive parameter sorting method combining static and dynamic parameters, and the image analysis sorting method. In addition, this paper analyzes the advantages and disadvantages of various sorting methods and the future development trend. The direct sorting method based on static parameters such as battery resistance, voltage, and residual capacity obtains highly accurate and reliable battery state

data information by fully charging and discharging the battery; however, this process consumes a lot of time and power and thus is no longer applicable to large-scale retired battery sorting tasks.

Indirect sorting method based on dynamic parameters, such as battery temperature, charging and discharging change curves, selects characteristic points from these parameters to assess the similarity between batteries using the Euclidean distance. This approach allows for battery sorting based on the similarity of curves, which can improve the consistency during operation[11]. However, the indices used in this method are relatively limited and cannot accurately and comprehensively reflect the characteristics of the batteries. To solve this problem, researchers have attempted to combine the static and dynamic parameters of the cells and tried to improve the accuracy of the sorting results by utilizing a multi-stage or comprehensive sorting strategy, which has been shown to have better consistency sorting results[52]. In addition to the above sorting methods, the image analysis sorting method for retired batteries detects batteries without damaging their structure. However, this method is highly dependent on data processing capabilities and the performance of detection equipment, and its high cost limits its widespread use at present.

In summary, future research on the consistency of retired battery sorting holds significant potential through methods based on the operational data. By utilizing historical data from retired lithium batteries and analyzing it with big data techniques, sorting criteria can be established to greatly improve the efficiency and accuracy of sorting. Therefore, the combination of big data with battery mechanism models, along with a multi-directional assessment of the battery static and dynamic parameters, and the use of artificial intelligence technology to optimize the consistency of retired battery sorting, represents the main direction of future research. In addition, in the future, we should focus on the innovation of non-destructive testing sorting technology, and actively explore new non-destructive testing principles and methods to realize the non-destructive evaluation of the internal structure and performance of retired lithium batteries and improve the value of battery cascade utilization.

(3) Combining these results, this paper further summarizes the progress and challenges in this field, gives insights into the latest technologies, and indicates potential future research directions, as shown in Figure 20. In addition, the residual capacity estimation and consistency sorting techniques for retired lithium batteries studied in this paper are of great significance in advancing the industrial processes related to spent batteries in the following four aspects:

• Optimize battery cascade utilization: In terms of battery cascade utilization, accurately estimating the remaining capacity and conducting consistency sorting can reasonably categorize retired batteries, and use those with better performance in scenarios with slightly lower performance requirements, such as distributed energy storage power stations, which not only extends the battery life and reduces costs, but also ensures the stability and safety of the battery pack performance.

• Improve the efficiency of battery recycling: For battery recycling, differentiated strategies are developed based on the remaining capacity to improve the targeting and efficiency of recycling, and consistency sorting facilitates a simplified recycling process and improves the resource recovery rate.

• Guarantee the quality of battery remanufacturing: In the battery remanufacturing process, these two technologies guarantee the quality and reliability of remanufactured batteries, reduce the rate of defective products and enhance market competitiveness.

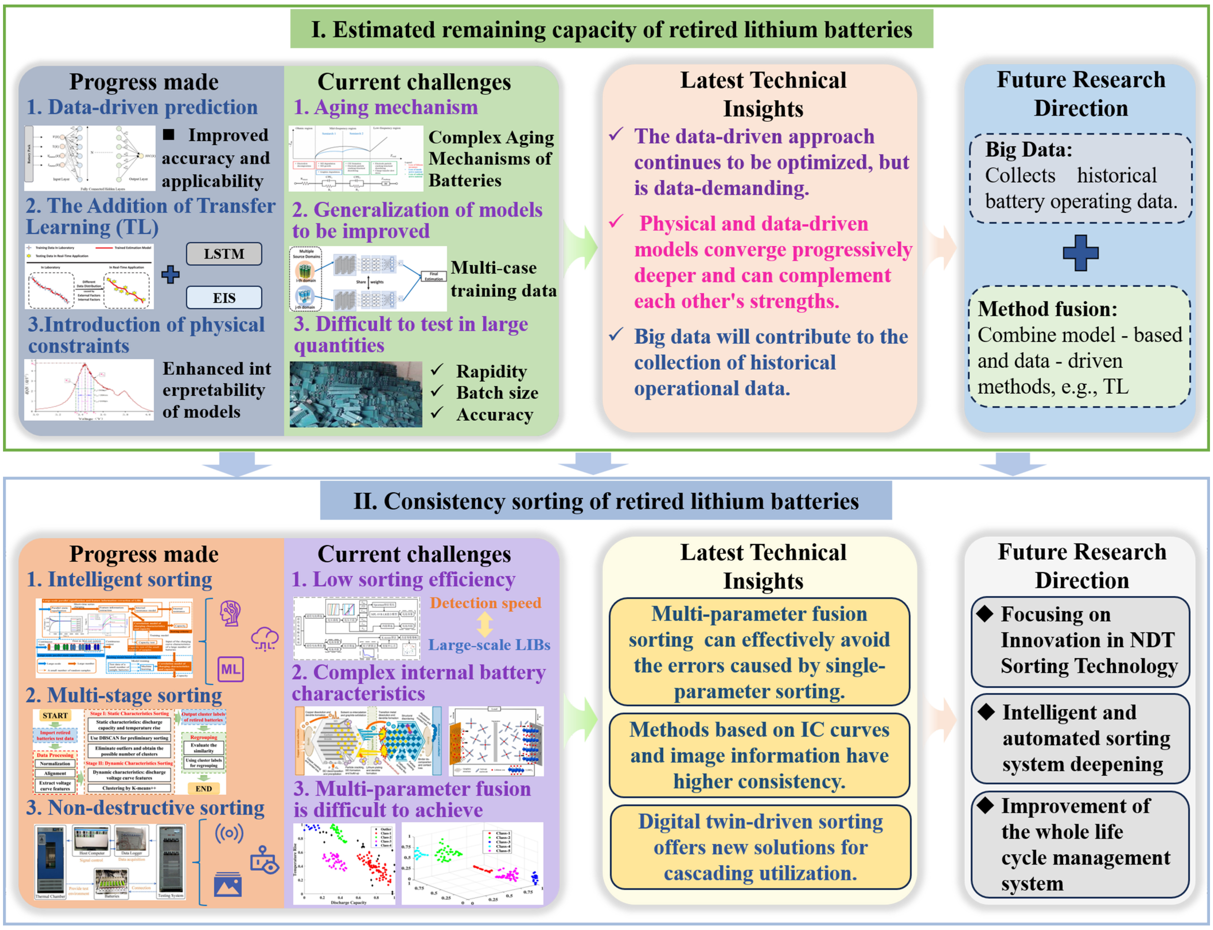


Figure 20. Progress and challenges of retired lithium battery cascade utilization, insights on latest technologies, and future research directions.

• Promote the establishment of industrial standards and norms: Their development promotes the establishment of industrial standards and norms. Unified standards are conducive to regulating the market order, promoting fair competition, facilitating government supervision, safeguarding consumer rights and interests and environmental safety, and contributing to the sustainable development of the battery industry in an all-round way.

DECLARATIONS

Authors' contributions

Writing - review and editing, writing - original draft, investigation, visualization: Kong, W.
Writing - original draft, conceptualization, investigation, methodology, visualization: Gong, W.
Writing - original draft, investigation, methodology, visualization: Liu, Z., Liu, J., Yang, H., Cheng, S.
Funding acquisition, supervision: Liu, W.
All authors read and approved the final manuscript.

Availability of data and materials

Not applicable.

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Conflict of interest

Liu, W. is an Editorial Board Member of the journal *Green Manufacturing Open* but was not involved in any steps of editorial processing, notably including reviewer selection, manuscript handling, or decision-making. The other authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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