




Review

Toward Group Applications: A Critical Review of the Classification Strategies of Lithium-Ion Batteries

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Received: 16 July 2020; Accepted: 28 August 2020; Published: 30 August 2020



Abstract: To solve the problems of the decreased reliability and safety of battery pack due to the inconsistency between batteries after single batteries are grouped is of great significance to find an appropriate sorting method of single batteries. This study systematically reviews the available literature on battery sorting applications for battery researchers and users. These methods can be roughly divided into three types: direct measurement, sorting based on the model, and sorting based on the material chemistry of batteries. Among them, direct measurement is about the direct measurement of the state parameters of batteries using some professional instruments or testing tools to sort and group batteries with similar or close parameters. Sorting based on the model classifies batteries into groups by establishing a battery equivalent model and carrying out model identification and parameter estimation with machine learning or artificial intelligence algorithm. Sorting based on the material chemistry of batteries is to explore some characteristics related to the chemical mechanism inside the battery. On the basis of reading extensive literature, the methods for classification of battery are provided with an in-depth explanation, and each corresponding strengths and weaknesses of these methods are analyzed. Finally, the future developments of advanced sorting algorithms and batteries prospect.

Keywords: battery sorting; battery grouping; method review; direct measurement method; equivalent model method; electrochemical analysis method

1. Introduction

With the rapid popularization of new energy vehicles, a single battery can no longer satisfy the needs of whole vehicle voltage and energy. Therefore, in the power battery system of new energy vehicles, single batteries need to be grouped, such as in series, in parallel, and in series-parallel, and applied to electric vehicles in the form of the battery pack. Power battery grouping technology has also become a technical bottleneck, restricting the marketization of electric vehicles. However, there are always some slight differences in the manufacturing process of single batteries, making it impossible for the capacity, internal resistance, and other parameters of the same model of batteries to be completely consistent [1]. Due to the limitation of the equipment and manufacturing process, this absolute difference between single batteries cannot be completely eliminated in a short time. Such kind of difference between single batteries is acknowledged as the inconsistency between single batteries after grouping, leading to a significant decline in battery life and failure to guarantee performance and safety [2]. When battery packs of new energy vehicles are used, the inconsistency

between single batteries inside the packs will be amplified with the increase of cycles, accelerating the aging of the packs. We are unable to change this difference between single batteries within a short time. Moreover, the method of improving battery cell linking technology has little significance for improving inconsistency [3]. There are still inconsistencies, even though new energy sources, such as supercapacitors, will be used in the future [4]. To improve the service life and utilization rate of batteries, we have to minimize this inconsistency between single batteries as far as possible and take an appropriate measure to sort batteries to be grouped in order to make the single batteries that are grouped as consistent as possible.

From another perspective, the popularization of new energy vehicles is bound to be accompanied by the retirement of more and more powerful battery packs of new energy vehicles. As predicted by the China Automotive Technology and Research Center, the accumulative scrap of power batteries of new energy vehicles in China will amount to 120,000–170,000 tons this year. How to deal with these retired batteries is a problem, demanding a prompt solution. At present, there are mainly two methods to deal with them. The first is to disassemble and recycle, that is, to discharge and disassemble the retired batteries, and then extract raw materials for recycling. Since the disassembled battery still has 60%–80% of the initial capacity, this method is not very economical. The second is to utilize them in cascade, that is, to use power batteries that are soon to be retired as a carrier of electric energy in fields like energy storage. This method can give full play to the remaining value of retired battery packs. The cascade utilization of power batteries refers to the detection, sorting, recombination, and reuse of retired batteries. If a single battery is directly recombined without being sorted, the service life of the battery pack will be greatly reduced and almost as poor as retired battery packs in severe cases. Therefore, to sort a single battery consistently is a key step in the cascade utilization of retired batteries.

With the gradual marketization of electric vehicles, there are increasingly pressing demands for battery sorting. Finding a more suitable sorting method has become a challenge. Scholars have proposed many distinct methods, while only a few pieces of reference [5–11] have summarized some of the methods. These reviews are splendid, while their summaries are not all-round enough. In this paper, some of the sorting methods of power batteries are reviewed and summarized according to the research direction. As illustrated in Figure 1, the author explores the advantages and disadvantages of different methods through a detailed analysis of the sorting bases of different methods, providing a reference for looking for a more effective sorting method of power batteries in the future; this can adapt to the development trend of battery manufacturing technologies.

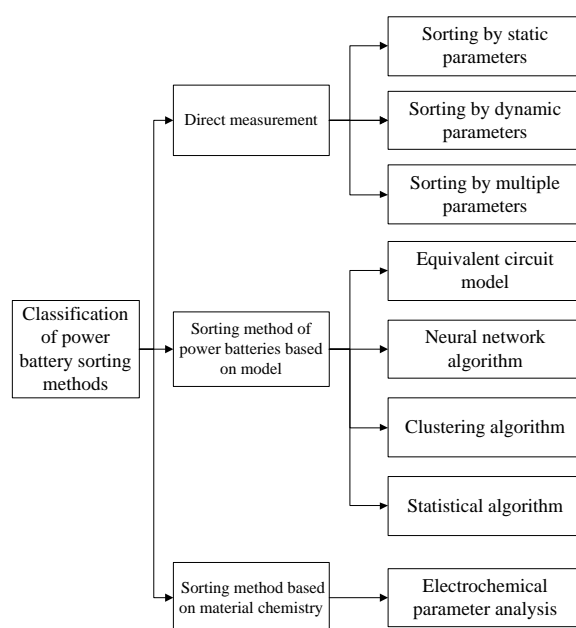


Figure 1. Summary of current power battery sorting methods.

The organizational structure of this paper is arranged as follows. Section 1 gives a brief introduction to the background of this article. Section 2 illustrates the sorting method of direct measurement. Section 3 introduces the sorting method of power batteries based on the model. Section 4 describe the sorting method relying on the material chemistry of power batteries. Section 5 compares and predicts the sorting methods of power batteries. Section 6 draws a conclusion.

2. Direct Measurement

The main parameters of power batteries include voltage, internal resistance, temperature, self-discharge rate, battery weight, and capacity decay rate. Traditional sorting methods sort batteries based on these parameters of power batteries, which can be divided into static parameters and dynamic parameters. Static parameters refer to parameters of batteries at a certain time point, namely, the parameters when batteries have no energy input or output. They are usually measured on batteries rather than in a working state. Dynamic parameters refer to the integration of parameters concerning time in a certain period, or the change of battery parameters in a period when there is energy input or output. This method sorts batteries by finding out similarities among single batteries depending on the characteristic of every single battery.

2.1. Sorting Based on the Static Parameters of Power Batteries

Static parameters refer to the state parameters of batteries when they are open or idle, that is, in the absence of energy input and output. Scholars in the industry generally believe that voltage, internal resistance, and capacity are the three parameters reflecting battery conditions best. Most sorting methods are also based on these three parameters to sort batteries. Feng Jianjun et al. conducted experiments on these three methods, and the results indicated that all three methods could be used as indicators for battery sorting. Figure 2 illustrates the voltage drop of a single battery in different storage periods. Figure 3 presents the influence of the consistency between the internal resistances of a single battery on battery grouping. Figure 4 exhibits the voltage difference between single batteries at different discharge rates [12].

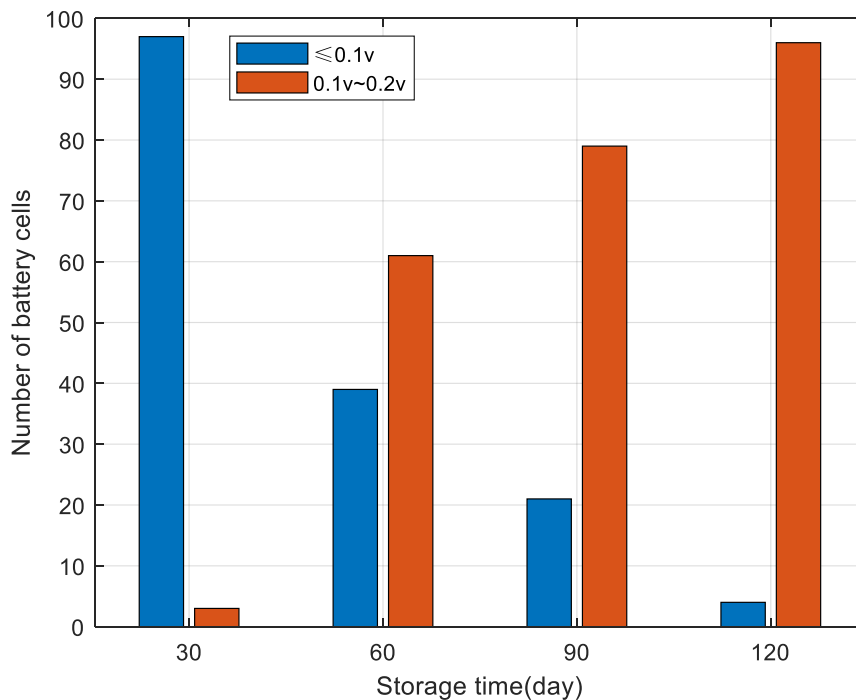


Figure 2. The voltage drop of battery cells in different storage periods.

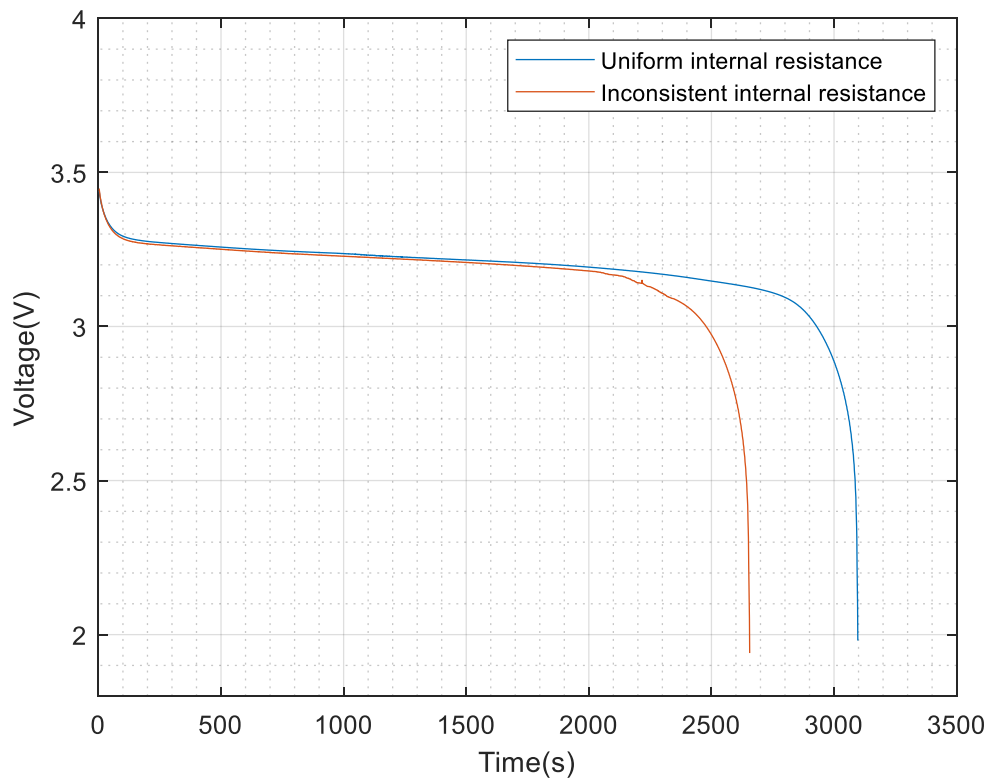


Figure 3. The influence of the consistency of the internal resistance of the battery cell on the battery group.

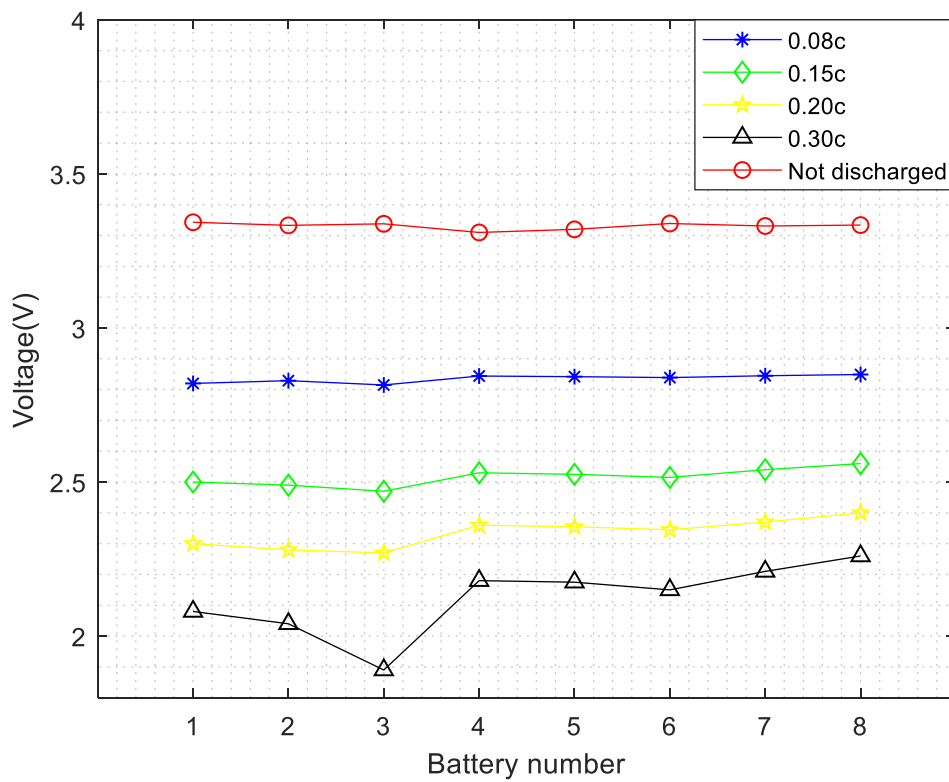


Figure 4. The voltage difference between individual cells at different discharge rates.

Apart from these three parameters, there are other parameters available for sorting, including the self-discharge rate of the battery. Sorting based on the static parameter of voltage typically puts a fully-charged battery on hold for dozens of days, and then its open-circuit voltage is measured.

Due to the different self-discharge rates between single batteries, these batteries are selected and sorted according to the open-circuit voltages before and after they are put on hold. Sorting based on the static parameter of internal resistance directly measures the internal resistance of battery using a professional instrument. Accurate measurement of the internal resistance of the battery requires high requirements on the test instrument and its method. This can increase the internal resistance of the battery. Sorting based on the static parameter of capacity often charges and discharges batteries under set conditions, identifies the capacity of batteries by the discharge current and discharge time, and then sorts batteries according to the capacity range identified. Besides, sorting based on static parameters is simple and easy to operate, while it can only demonstrate that the batteries are consistent under set conditions. In actual work, the conditions of batteries are complex, and this method cannot reflect the working characteristics of batteries. Therefore, it is subject to certain limitations and is often used as a means of primary selection before sorting or applied to a sorting machine or system. Reference [13] sorts batteries according to the weight of the battery. References [14–16] adopt a sorting system based on voltage. References [17–19] use a sorting device based on internal resistance. Reference [20] employs a sorting system based on capacity. Reference [21] designs a field-programmable gate array (FPGA) fast sorting system based on the voltage and impedance of battery, contributing to a significant improvement of the sorting efficiency.

The kind of sorting, that is, sorting based on the main characteristic parameters of a single battery, such as voltage, internal resistance, and capacity, allows the easy measurement and quick sorting. It can realize sorting with simple testing tools; for example, a multimeter is very suitable for scenarios with low sorting requirements. This method is also a mainstream process in recent years, adopted by battery manufacturers before delivering battery products out of the factory.

2.2. Sorting Based on the Dynamic Parameters of Power Batteries

Different from sorting by static parameters, sorting by dynamic parameters is based on the parameters of a single battery in the presence of energy input or output. This method is closer to the normal working state of batteries. It sorts batteries by finding out the same parameters between single batteries, such as dynamic internal resistance and volt-ampere (VA) characteristic curve, through different energy inputs or outputs of batteries. References [22–27] group batteries by comparing the variation of positive VA characteristics and charge-discharge characteristic curves of different single batteries and selecting single batteries with the same curves. Figure 5 presents the discharge characteristic curves of batteries that satisfy sorting conditions. There are seven single batteries curves in Figure 5. Thus, the closest battery curve is matched into a group, which is divided into group 1 and group 2. Reference [28] sorts batteries by comparing the capacity increment curves of different single batteries. References [29–31] sort batteries by selecting dynamic voltage parameters in a certain state of charge (SOC). An experiment in reference [32] demonstrates that the consistency between the dynamic characteristics of batteries mainly depends on the consistency between low-frequency impedance of batteries. References [33,34] sort batteries by extracting feature points. Reference [35] defines the concept of available capacity through the relationship between battery capacity and impedance spectroscopy and sorts batteries based on available capacity. References [36] sort single batteries by connecting them in series. Reference [37] uses the same current to circulate the series battery pack at the same time to quickly realize the battery classification. Reference [38] adopts electrochemical impedance spectroscopy (EIS) as an indicator of classification. Single batteries are first connected in series and then charged, discharged, and sorted by charge-discharge curves. This method also achieves certain success.

The static parameters mainly focus on the parameter characterization of the battery at a certain moment. For example, the battery's voltage, current, internal resistance, and other parameters can be directly obtained through the battery test device when the battery is in a static state. The static parameters can also be understood as the parameters at this moment. Static sorting is to use the difference of the parameters at the moment for classification.

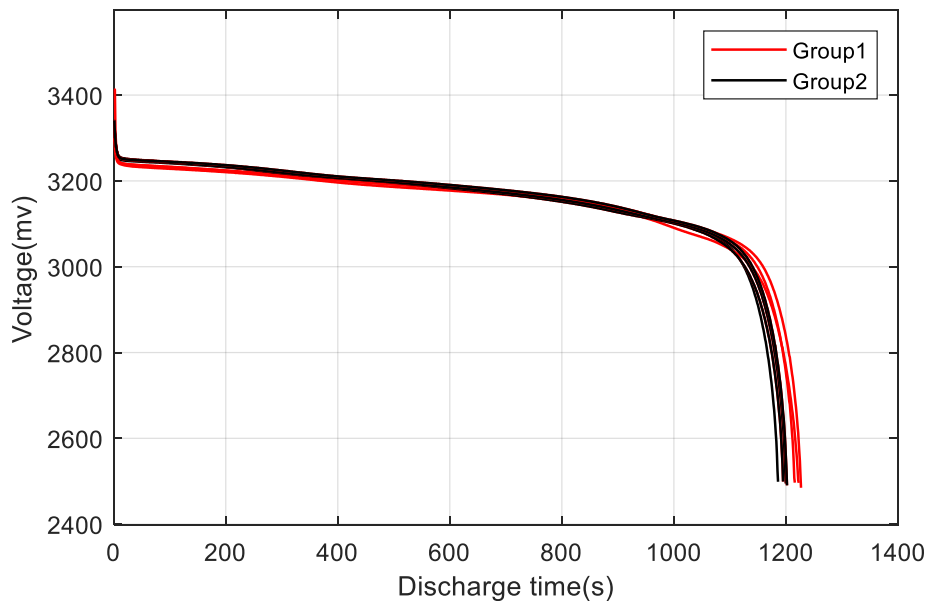


Figure 5. The discharge curve of the battery that meets the sorting conditions.

The dynamic parameters are evolved based on static parameters and focus more on the characteristic parameters of the battery over time. According to the rate of change over time, the parameters used in dynamic sorting may not include all the parameters at time T and may also include $T-1$, $T-2$, and more parameters of the changing process. Compared with static sorting, dynamic sorting pays more attention to the rate of change of battery parameters during the use period. It solves the input and output conditions of battery energy that are not involved in sorting by static parameters and can better reflect the actual service condition of batteries. Particularly, this method significantly improves the service life of battery packs, is well-received by battery manufacturers, and gradually replaces sorting by static parameters.

2.3. Sorting by Multiple Parameters

Sorting by multiple parameters selects qualified single batteries based on such parameters as discharge capacity, self-discharge rate, and internal resistance. These parameters can be either static or dynamic. Sorting by multiple parameters selects a wide range of parameters. Therefore, it is more comprehensive compared with sorting by dynamic parameters and sorting by static parameters, and the single batteries it sorts can almost form battery packs with preferable consistency. Although this method has high accuracy, it has obvious shortcomings, such as complicated operation, low efficiency, and long sorting cycle. References [39–65] analyze the changes in some key parameters, that is, capacity, EIS, energy (voltage or temperature), and internal resistance, during the discharge of batteries, reveal the regularity of changes of curves, and compare changes of parameters and dynamic characteristic curves, completing the sorting of batteries in combination with different functions. Among them, reference [40] sorts batteries by establishing the three-dimensional coordinates of capacity, voltage, and internal resistance, selects different parameter influence factors, and evaluates their diversity factor. Reference [41] sorts and utilizes retired batteries in cascade through the relationship between internal resistance and state of charge (SOC) and the relationship between temperature and charge-discharge rates. Reference [42] first adopts sorting by multiple static parameters to sort batteries using static parameters, such as capacity, internal resistance, voltage, self-discharge rate, and date of manufacture, and then simulates the actual working conditions of power battery packs to test the charge, discharge, and aging of batteries. Based on static parameters, it takes dynamic parameters into account and improves the sorting accuracy. Reference [66] screens the retired batteries of electric vehicles with the combination of pulse characteristic curve and electrochemical impedance spectroscopy.

References [67,68] carefully consider many factors affecting the consistency of a single battery and conduct careful sorting.

Sorting by multiple parameters is a combination of sorting by dynamic parameters and sorting by static parameters. As illustrated in Figure 6, it increases sorting parameters and conditions, resulting in guaranteeing the sorting accuracy. However, this method is not suitable for battery manufacturers' mass sorting due to the high complexity of the sorting process, long sorting cycle, and low efficiency. However, sorting by multiple parameters has high utility value if it is applied to aerospace, military industry, and other fields that require high accuracy and long service life of the battery pack.

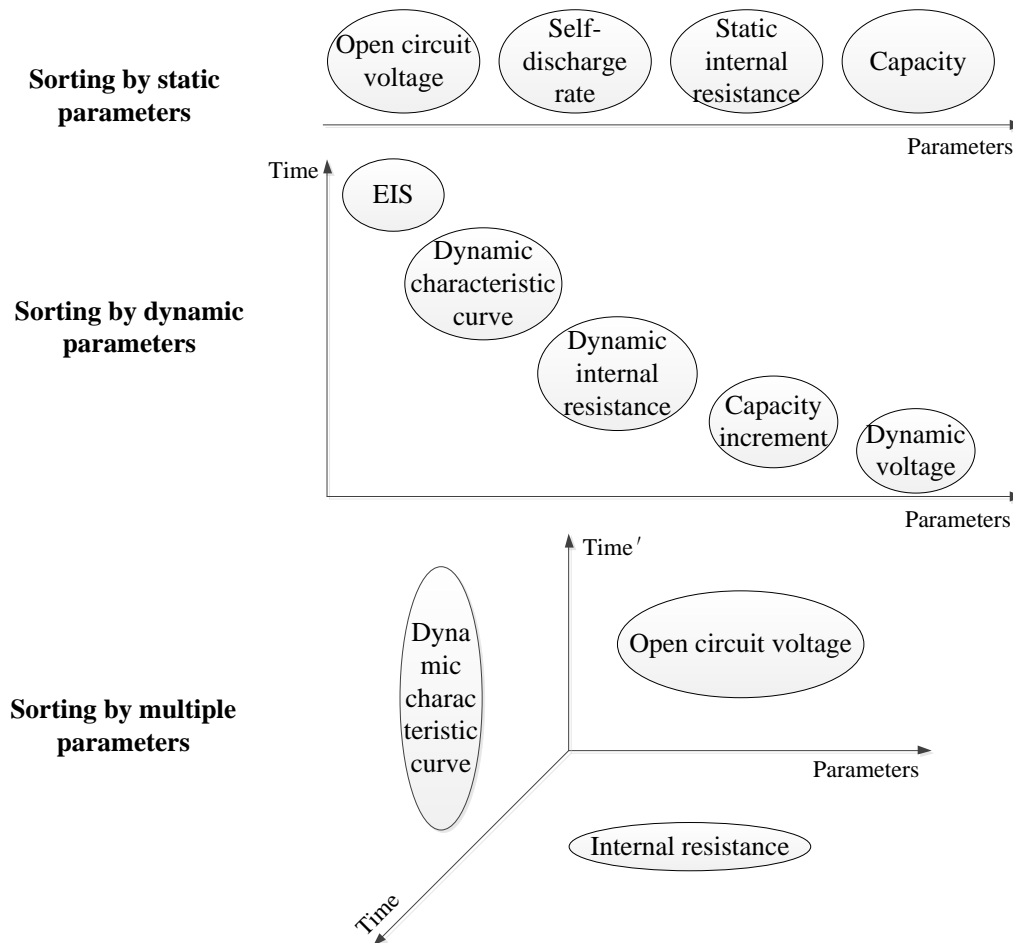


Figure 6. The discharge curve of the battery that meets the sorting conditions.

3. Sorting Method of Power Batteries Based on Model

This sorting method sorts batteries by establishing a model with all kinds of algorithms or measurement methods based on the internal mechanism of batteries or machine learning. The most common clustering algorithm for sorting is an unconventional one, which first assumes that a known data set satisfies a certain model and then finds out a model conforming to the data distribution. Figure 7 exhibits a flowchart for sorting based on the model. During the training of the model, the number of clusters can be determined dynamically. Through the training of the model, the preset samples are divided into clusters, and data points with similar characteristics in the clusters are grouped as one cluster; thus, data clustering is completed. No matter the clustering algorithm is used or not, modeling is a convenient and fast method. Some complex methods tend to finish sorting by establishing various models.

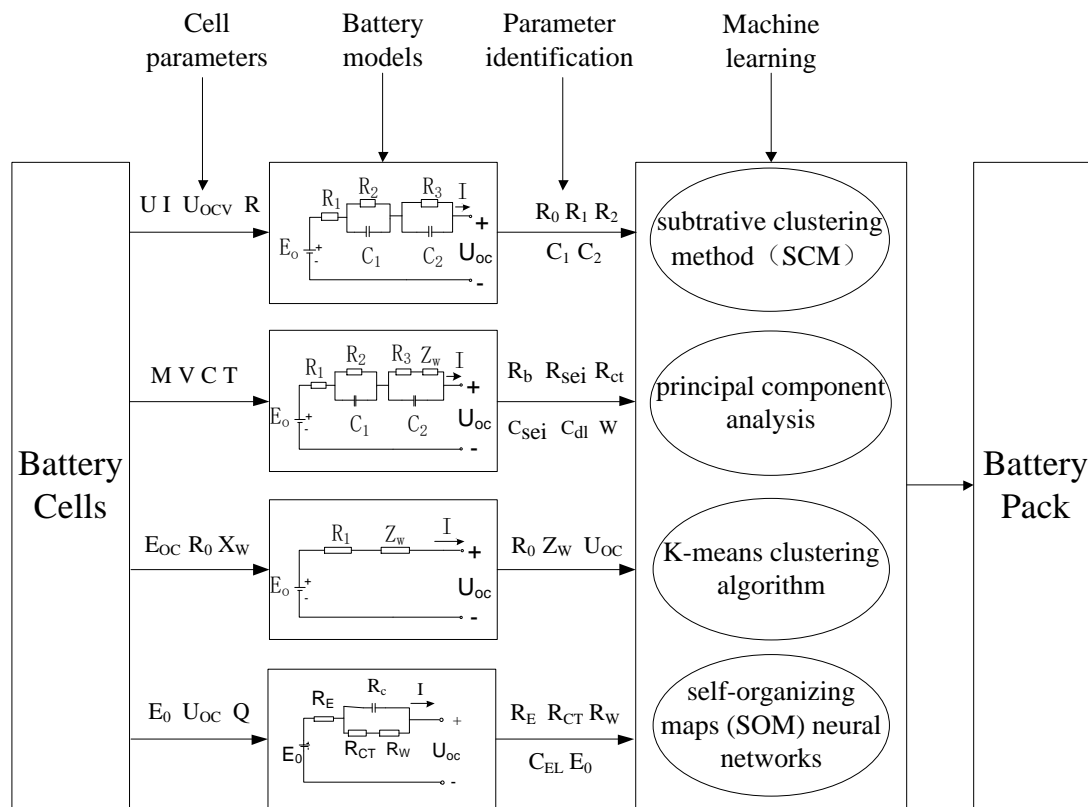


Figure 7. Schematic diagram of the model-based battery sorting method.

3.1. Equivalent Circuit Model

The equivalent circuit model is a model reflecting the internal mechanism of battery by combining capacitor, inductor, and resistor into different circuits. During battery sorting, equivalent circuit models, such as the equivalent circuits of electrochemical impedance spectroscopy and battery module, are often used. Electrochemical impedance spectroscopy is a technology that can simulate the electrochemical system of batteries. By applying an alternating current potential wave with different frequencies and a small amplitude to the electrochemical system, the internal mechanism of the battery can be further explored without damaging that battery. Electrochemical impedance spectroscopy is often used based on the equivalent circuit model. This equivalent circuit model is composed of basic components, such as resistance (R), capacitance (C), and inductance (L), which are connected in series and parallel. Sorting is completed by measuring the impedance in the equivalent circuit model and simulating the impedance spectroscopy curve using the measurements. Figures 8 and 9 illustrate the second-order Randles equivalent circuit model and the Thevenin equivalent circuit model, which are commonly used in sorting. The equivalent circuit model approximately represents some phenomena inside the battery. In Figure 8, R_e represents the ohmic internal resistance, and R_{ct} and R_w represent the charge transfer internal resistance and polarization internal resistance, C_{dl} represents the electric double-layer capacitance, and in Figure 9, R_1 represents the ohmic polarization process, R_2C_1 represents the electrochemical polarization phenomenon. In the equivalent circuit model of the battery module, the model simulates the aging process of battery and the changes in such parameters as internal resistance and capacity, contributing to the identification of the influence of different parameters on the sorting [69]. Based on the electrochemical impedance spectroscopy, references [70–72] select the characteristic frequency responses of several characteristic points of impedance spectroscopy curve to complete sorting. Reference [73] sorts batteries by establishing an equivalent circuit model first and then uses an solid electrolyte interphase (SEI) film growth model to derive the self-discharge rate.

Reference [74] proposes a method to make the battery pack reach its maximum initial capacity and uses the equivalent circuit model to analyze the dynamic modeling of the battery pack.

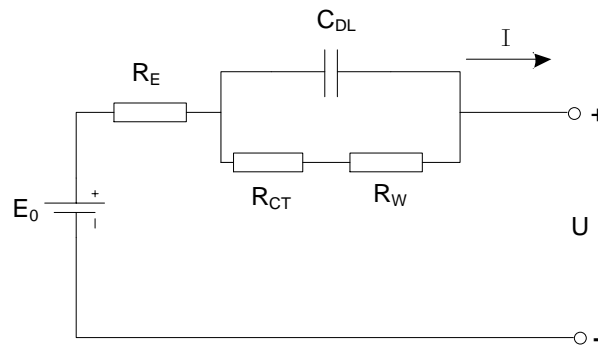


Figure 8. Second-order Randles equivalent circuit model.

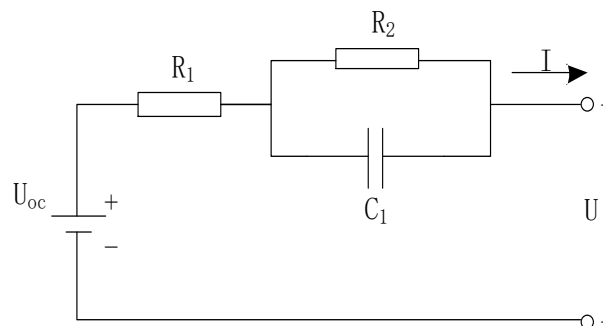


Figure 9. Thevenin equivalent circuit model.

Although it is hard for an equivalent circuit model to sort directly, it can serve as a springboard of many complex sorting methods. For different sorting methods, how to select an appropriate equivalent circuit model and how to optimize this model to make it more applicable to sorting is a direction worth exploring, regarding equivalent circuit models applied to battery sorting.

3.2. Clustering Algorithm

The clustering algorithm is unsupervised. If it is difficult to classify data at the beginning, the algorithm can judge the similarity between data at its discretion and cluster together similar data. Common clustering algorithms for battery sorting include K-means, fuzzy C-means (FCM), and system clustering. In battery sorting, sorting parameters are first selected. A reasonable selection of parameters can make the clustering results more accurate. Reference [75] selects three algorithms to compare, including principal component analysis, kernel principal component analysis, and random forest, and ultimately verifies that random forest (RF) has the best sorting effect. References [76–81] adopt K-means, take a variety of factors into account, and demonstrate that it has high reliability. Reference [82] uses k-means to judge the condition of charging facilities. References [83,84] employ improved K-means algorithms based on the characteristic distribution model and the EIS model. Experimentally, this improved algorithm greatly improves the sorting results compared with the traditional K-means algorithm. Reference [1] adopts a subtractive clustering sorting method based on the sorting index of feature points on the charge-discharge curve. Reference [85] uses a combination of factor analysis and systematic clustering. Both methods are worthy of reference. References [86–90] sort batteries based on the discharge voltage platform of battery, combined with FCM. References [91–93] employ the combination of FCM and support vector machines to complete sorting and obtain good results. References [94,95] propose a new sorting method of lithium batteries based on improved FCM. Reference [96] uses a combination of multi-parameter sorting and FCM to complete battery

sorting. Reference [97] uses the multi-step FCM algorithm (MSFCM). The method uses the clustering validity function to determine the optimal class number, two times of FCM sorting algorithm in optimal results, using an extrusion algorithm. Reference [98] uses a combination of FCM and particle swarm optimization algorithm-least squares support vector machine (PSO-LSSVM) for battery sorting; the method breaks the limitation of building battery classification model based on prior knowledge, reduces the dependence on parameter selection, and enhances model training speed and accuracy. Reference [99] clusters charge-discharge characteristic curves to finish sorting. Reference [100] clusters and sorts batteries using distance approach and correlation coefficient approach. Reference [101] proposes a fast battery sorting method based on hierarchical clustering, with the state voltages and state resistances at different discharge rates as the indexes. Experiments have indicated that this method can greatly improve sorting efficiency. Reference [102] uses a battery grouping method based on time series clustering for sorting. Reference [103] proposes a retired battery clustering algorithm based on traversal optimization for sorting. This method does not need to define the number and center of clusters in advance and has immunity to outliers. Reference [104] employs a novel grouping scheme based on distributed time series clustering and uses cloud data to achieve rapid battery grouping, which not only reduces time costs but also improves sorting efficiency.

In this paper, the actual applications of the clustering algorithm are introduced by taking the most commonly-used algorithm, fuzzy C-means (FCM), as an example. FCM clustering algorithm is an unsupervised machine learning method calculating in Euclidean space and determines the object of optimization by calculating the geometric distance from each battery parameter to the clustering center. Afterward, the membership matrix of sample data is obtained using iterative operation. According to the membership degree of each objective in the membership, it classifies objects with the greatest similarity possible into one category.

The specific steps of fuzzy C-means FCM algorithm are described as follows:

1. Initialize the clustering center or membership matrix U ; set the number of clusters C and fuzzy index m ; randomly initialize $V(0)$; set the precision of convergence ε ; let the number of iterations $k = 0$;
2. Calculate the membership matrix $U(k + 1)$;
3. Calculate the clustering center $V(k + 1)$, let $k = k + 1$.

Repeat steps 2 and 3 until the following termination conditions are met:

$$\|V^{(k)} - V^{(k-1)}\| \leq \varepsilon, k \geq 1$$

Depending on the number of clusters, the final classification results may vary. Figure 10 exhibits the clustering results when the number of clusters is 2, 3, and 4.

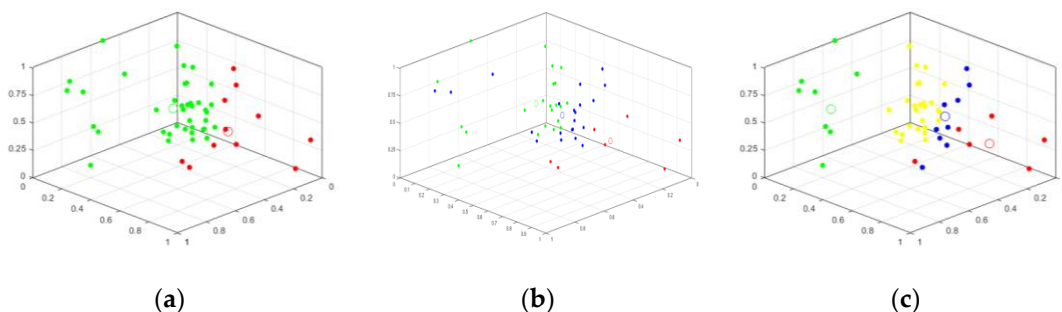


Figure 10. Clustering results of different number of clusters: (a) Number of clusters $C = 2$; (b) Number of clusters $C = 3$; (c) Number of clusters $C = 4$.

The sorting results obtained using clustering algorithms are accurate; however, the effect is not so ideal and needs improvements in many aspects when many clustering algorithms are applied to

battery sorting directly. On the other hand, clustering algorithms generally have high complexity and are sometimes caught up in a local optimum. How to improve the algorithm, perfect the model, and reduce the complexity to make them be applied to large-scale mass sorting is a direction worthy of exploration in the future.

3.3. Neural Network Algorithm

A neural network algorithm is a process of reasoning based on logical rules. It is generally composed of an input layer, a hidden layer, and an output layer. Typically, we select several sets of battery parameters as the input layer of the neural network. Reference [105], for example, employs neural networks to control battery power. Reference [106] inputs voltage, capacity, and internal resistance (as input parameters) into a backpropagation (BP) neural network model. Reference [53] conducts a comparative analysis of the conventional algorithm and neural network model, concluding that sorting based on a neural network algorithm is more beneficial. References [107–111] adopt a self-organizing map (SOM) model based on artificial neural networks to sort batteries. This method can be used through parameter identification of the equivalent circuit model or by directly obtaining a battery parameter, to adapt to the weights and find out the optimal solution. For example, reference [110] classifies nickel-metal hydride (Ni-MH) batteries according to their charging thermal behaviors. In this SOM neural network model, the job of neurons is to map data from a high dimension to a low dimension, falling into the domain of the feed-forward neural network. Reference [112] uses a fast capacity estimation method based on a neural network model to achieve fast battery sorting. Reference [113] proposes a genetic algorithm based on partial discharge curves and a back-propagation (GA-BP) neural network for retired battery screening methods and achieves good results. Different from clustering algorithms, neural network algorithms can be either supervised or unsupervised. For example, the self-organizing neural network (SOM) commonly used in battery sorting is an unsupervised algorithm. This model can identify similar vectors through the topology and distribution of all vectors that are input to it. The schematic of the SOM model applicable to sorting is illustrated in Figure 11. P_i represents the input vector of the model. The number of input vectors of each battery can be identified according to battery parameters. If the surface temperature of the battery at the end of charging at three different rates is taken as the sorting parameter, the number of input vectors is three. The neurons in the hidden layer perform the main classification task. After each input vector, there is a weight vector (w_i) connected to it and a bias vector (u) with a constant value; a , b , and c following them represent three neurons corresponding to the output types I, II, and III, respectively.

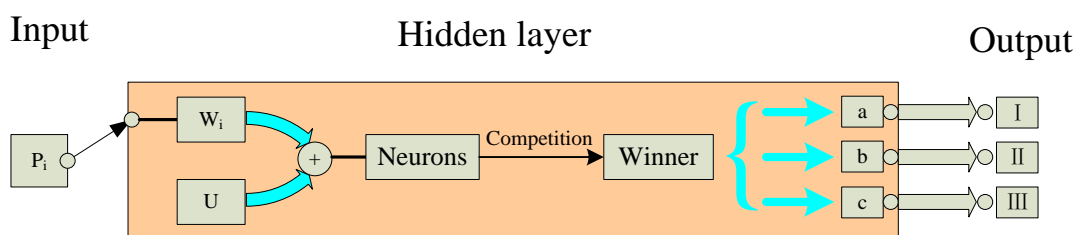


Figure 11. Schematic diagram of the self-organizing model (SOM) applied to batteries sorting.

The neural network algorithm is widely used, while SOM neural network algorithm is subject to some limitations. For example, it can easily be caught up in a local minimum when the initial conditions are poor. Therefore, we can conduct in-depth research on the self-organizing feature map (SOFM) neural network algorithm, an improved version of the SOM neural network algorithm. Perhaps there will be a certain breakthrough when it is applied to battery sorting. Besides, some neural network algorithms have not been applied to battery sorting. For example, reference [114] uses genetic algorithm to optimize the battery grouping topology, thereby reducing the cost of battery packs and increasing life, reference [115] uses a deep convolutional neural network (DCNN) to

estimate long-term battery cycle data, reference [116] is based on the DCNN algorithm to measure the voltage, current, and charging capacity of a part of the charging cycle, so as to realize the capacity estimation of the battery, reference [117] uses a combined convolutional neural network (CNN) to infer the state of charge (SOC) of the battery, and reference [118] uses the feed forward neural networks (FFNN) model and the extended Kalman filter algorithm to implement SOC estimation. Reference [119] employs a feed-forward neural network, convolutional neural network, and long short-term memory to estimate battery capacity and health status. Reference [120] uses long short-term memory (LSTM) recurrent neural network to predict the synchronous multi-parameters of the battery system. Reference [121] proposes a stacked bidirectional long short-term memory (SBLSTM) neural network for SOC estimation. Reference [122] adopts a genetic algorithm (GA) and convolutional neural network (CNN) to form a battery SOC prediction model of GA-CNN to estimate SOC. Reference [123] utilizes a deep neural network (DNN) method to predict the state of health (SOH) and remaining useful life (RUL). Reference [124] proposes an integrated deep learning method for lithium-ion battery RUL prediction by integrating an autoencoder with a deep neural network (DNN). Reference [125] proposes a method based on support vector regression (SVR) to accurately predict the RUL. Reference [126] realizes battery SOH prediction based on the gated recurrent unit (GRU). Reference [127] estimates battery parameters based on a deep Bayesian neural network. References [128] uses the deep Gaussian process algorithm to realize the health monitoring of lithium-ion batteries. Apparently, there are many deep learning methods, and we cannot list all of them here. In the near future, more and more deep learning methods will be applied to battery sorting, opening a brand-new door for battery sorting technology.

3.4. Statistical Methods

There are many sorting methods based on statistical principles. The commonly-used ones, such as principal component analysis and fuzzy Bayesian approach, all belong to statistical methods. There are so many methods that will not be enumerated here. This paper mainly expounds on several statistical principles that are commonly used in battery sorting, as well as algorithms that can be applied to battery sorting in the future. In the process of the static grouping of power batteries based on the statistical model, by comparing open-circuit voltage and internal resistance curves of batteries, Zhang Chenbin et al. [129] verified that their parameter characteristics conformed to the normal distribution, as illustrated in Figure 12. Reference [130] uses fuzzy iterative SOM data analysis technique to perform a fuzzy clustering analysis on the parameters of battery samples through principal component analysis. Reference [131] compares the traditional sorting method, principal factor sorting, and total factor sorting; an experiment reveals that the sorting effect is the best when batteries are first sorted by total factor and then sorted by dynamic parameters. Reference [132] realizes battery sorting through the sorting algorithm of discharge capacity and the second threshold of the average amplitude of charging voltage. Reference [133] conducts a comparison of fuzzy rules and a traditional multi-criteria evolutionary algorithm and identifies a battery sorter, contributing to increasing the service life of batteries. According to the resistance, voltage, and other parameters that are input, reference [134] obtains a comparand and sorts batteries by comparing each of them to this comparand. Using mathematical methods, reference [135] extracts key points of battery performance to complete sorting. Based on the capacity and internal resistance parameters, reference [136] uses mathematical models for sorting batteries. Reference [137] employs the Delphi method and gray correlation analysis to sort batteries. References [138] adopts capacity-based statistical models for sorting batteries. Reference [139] adopts the cycle probability prediction algorithm to predict the battery cycle life. Reference [140], according to capacity distribution, order statistics, central limit theorem, and converter efficiency, optimizes energy efficiency by finding the best number of cells in a battery pack. Reference [141] analyzes the evaluation method of battery sorting from the perspective of capacity and internal resistance, combined with mathematical analysis, and proposes an accurate battery selection strategy.

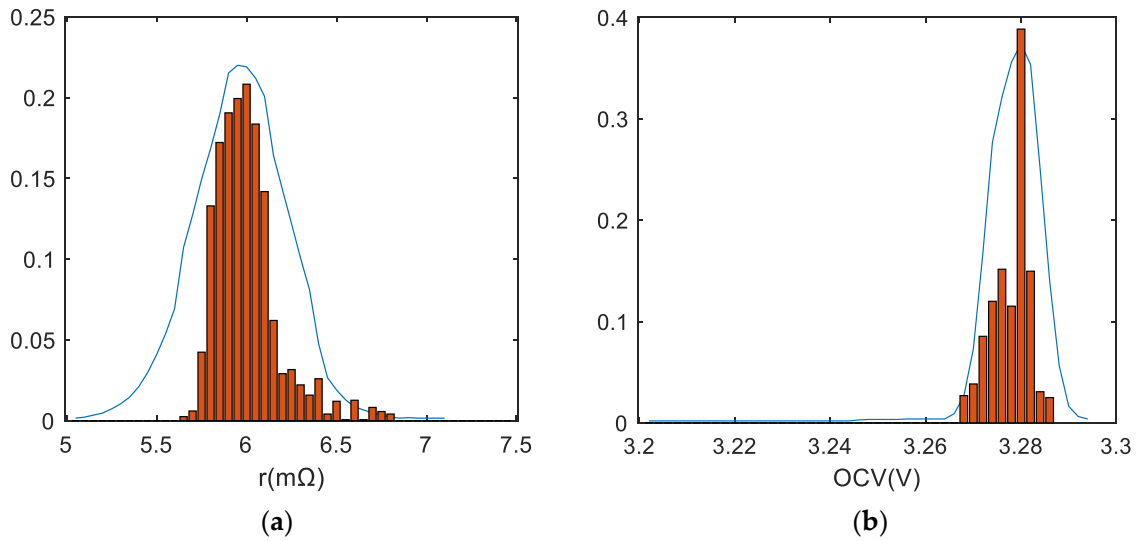


Figure 12. (a) Statistical distribution curve of open-circuit voltage for a group of cells; (b) Statistical distribution curve of internal resistance of a group of cells.

Many statistical methods have achieved remarkable success in other aspects, such as decision tree classification based on particle swarm optimization algorithm, text classification based on deep convolutional neural network, and remote sensing image classification based on linear regression. Regarding battery sorting, all of these methods can be improved and utilized. For example, Figure 13 presents a linear least squares estimation diagram of the parameters of lithium iron phosphate battery samples [142]. It may be difficult to optimize the statistical algorithm in the future. We may improve the model, analyze other statistical algorithms, fit them into battery sorting, and combine them with new techniques, such as cloud servers and big data, to lower the requirements for sorting equipment and improve the sorting efficiency. Figure 14 illustrates a schematic diagram of a sorting method with feedback. The model can be trained faster due to the feedback link and is a preferable choice for the model-based sorting method.

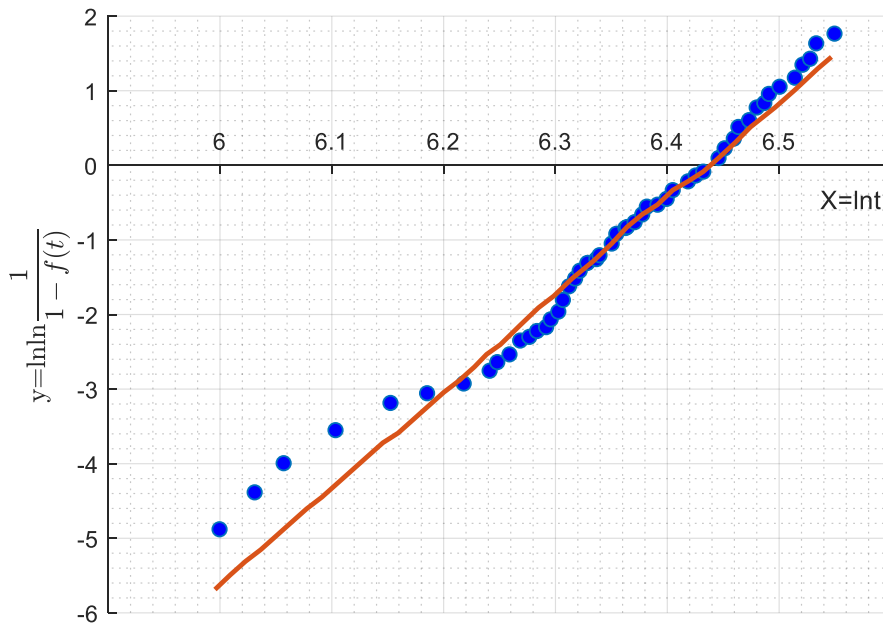


Figure 13. Linear least square estimation diagram of lithium iron phosphate battery.

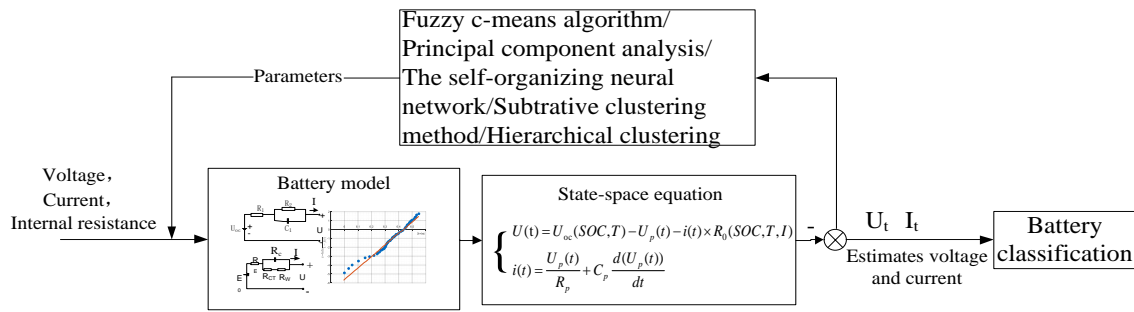


Figure 14. Schematic diagram of the identification model parameter flow with feedback.

4. Sorting Method Based on Material Chemistry

Both the direct measurement method and the model-based sorting method are sorted based on various external parameters of the battery, and the internal situation of the battery is not involved; in other words, the battery is just regarded as a “black box”. The method based on battery material chemistry is to start from the working principle of the battery and find the relevant electrochemical parameters involved in the chemical reaction of the battery. However, it is hard to have a thorough understanding of the internal mechanism of the battery without damaging the battery, and most of the electrochemical parameters are difficult to measure without damaging the battery. Therefore, we have adopted two solutions: easy to use measured electrochemical parameters or build an electrochemical model.

When the charge-discharge voltage is confined to a certain range, Coulombic efficiency can be regarded as the proportion of the number of remaining reversible lithium-ion to that of initial lithium-ion participating in the current cycle, in a constant current single cycle test. Figure 15 exhibits the relationship between the number of cycles and Coulombic efficiency. Besides, Coulombic inefficiency (CI) is the proportion of the number of remaining irreversible lithium-ion to that of initial lithium-ion participating in the current cycle. It is verified through subsequent tests that there are some relationships between the number of cycles and Coulombic inefficiency. Coulombic inefficiency can be used as a screening index for the cascade utilization of batteries [143].

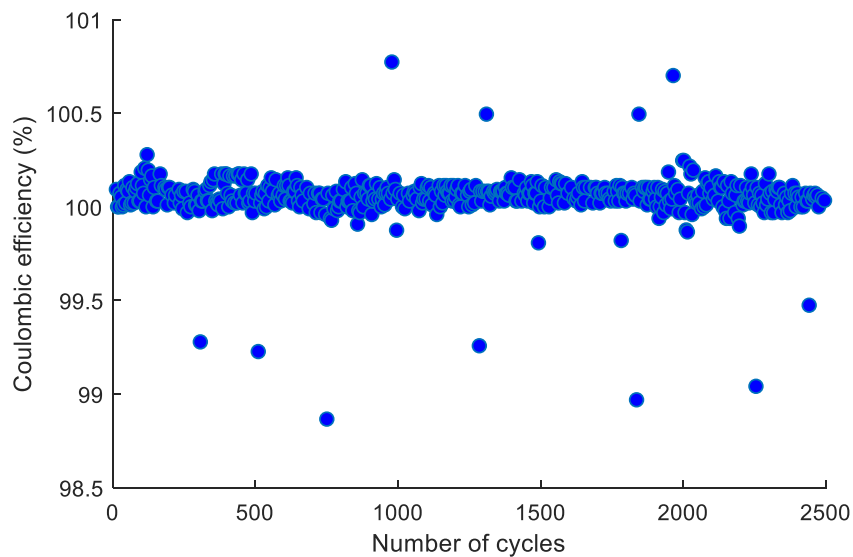


Figure 15. Relationship between the number of cycles and Coulombic efficiency.

By establishing an electrochemical model, we can simulate the internal working state of the battery to determine some electrochemical parameters that we cannot directly measure. References [144,145] analyze the aging of the battery by forming an electrochemical model. Reference [146] combines

the electrochemical model with CNN to judge the state of some parameters (such as solid particle conductivity, solid particle areas, and solid electrolyte interface layer thickness) inside the battery. Owing to relatively few sorting methods based on the material chemistry of the battery, we can conduct in-depth studies in this regard and find more suitable electrochemical parameters for sorting batteries. In the future, it is an acceptable choice to combine sorting methods based on materials chemistry with emerging algorithms, such as deep learning.

5. Comparison and Prospect

Among the numerous sorting methods, direct measurement is the simplest and most direct one. Direct measurement includes the measurement of static parameters, dynamic parameters, and multiple parameters. The external characteristic parameters of batteries (usually including voltage, internal resistance, and self-discharge rate) can be measured with different methods. Generally, only static parameters or dynamic parameters are used for rough sorting. Nevertheless, multiple conditions can be used for sorting batteries if there is a high requirement for battery packs. The sorting method of direct measurement is the basis of other sorting methods. Although direct sorting by some parameters has a poor effect, it is still of certain research value. For example, some parameters of battery are hard to be measured, or batteries may be easily damaged during measurement. Under this circumstance, we can measure these parameters by scanning batteries directly with ultrasound or X-ray, which can significantly reduce the time required by sorting. Alternatively, we can find one or more parameters suitable for sorting all battery types, preventing the influence of different battery types on sorting.

Sorting based on the model sorts batteries and can be completed by establishing a model and applying various algorithms or means. Compared with direct measurement, sorting based on the model is more accurate and efficient. By setting up the model, all kinds of algorithms can be realized, such as neural network algorithms, clustering algorithms, and statistical algorithms. They can lower researchers' reliance on actual batteries and easily adapt to different types of batteries. Such methods are usually accurate, while they cannot be directly used in battery sorting. A vast majority of scholars adopt improved algorithms to enhance the accuracy and stability of battery sorting. With the popularization of big data, cloud computing, cloud storage, and other emerging technologies, we can combine them with some algorithms to achieve faster sorting. Moreover, we can also realize high-precision sorting by increasing the dimensions of calculation or using multiple algorithms concurrently. With the advent of the 5G era, an online sorting platform can be established, a database can be set up on the cloud side, and single batteries that can be grouped can be directly found according to the data input.

From the perspective of the material chemistry of batteries, sorting based on the material chemistry of batteries is performed by their internal electrochemical mechanism. In general, power batteries, the direct conversion of chemical energy into electric energy, are the result of spontaneous chemical reactions inside batteries, such as oxidation and reduction. The internal mechanism of a battery can reflect the parameters of this battery in a more intuitive way, such as the performance and cycle efficiency. For example, the decay rate of the service life of lithium batteries can be analyzed by judging the number of reversible lithium-ion. Relatively, this approach is more suitable for sorting the cascade utilization of batteries. Due to the lack of research data on the material chemistry of batteries, we can conduct more studies from this aspect in the future and sort batteries by some electrochemical parameters. Moreover, the working principles of different types of batteries are almost the same. Thus, this method has high transferability. Once the technology becomes mature, it can be applied to various types of batteries. This sorting method has significant potential and is worthy of exploration and practice by researchers.

Most of the above methods can be used in either battery grouping or sorting for the cascade utilization of batteries. Due to the extremely harsh operating conditions of electric vehicles, the temperature, self-discharge rate, electrolyte density, and other parameters of every single battery inside the battery pack are not the same during operation, making it difficult to guarantee the balance of batteries. Therefore, the sorting of power batteries before grouping is simply to ensure the good

working conditions of power batteries. To reduce the increase of difference among single batteries inside the pack during operation is also one of the complications that we should focus on in the future. Systematic theories and methods are needed for real-time diagnosis of battery packs with strong time-varying and heterogeneous properties. A comparison of these three main methods is presented in Table 1.

Table 1. Comparison of power battery sorting methods.

Method	Advantage	Disadvantages	Direction of Development
Sorting by static parameters	The simplest and most direct method; wide range of application; fast sorting speed.	Measure; cannot reflect battery operating characteristics.	Improve measurement methods and accuracy.
Sorting by dynamic parameters	It can partially reflect the characteristics of the battery during operation; compared with static parameter sorting, the accuracy is higher.	It is easy to cause damage to the battery; it can only reflect the parameters of the set working conditions, and it is difficult to determine the actual working parameters.	Dynamic parameters should be as close as possible to the actual situation; reduce the impact of the test on the battery.
Sorting by multiple parameters	The sorting accuracy is high; the consideration conditions are more comprehensive.	There are many sorting processes and long-time consumption; it is difficult to achieve large-scale sorting.	Reduce unnecessary processes and improve sorting efficiency.
Equivalent circuit model	It can reflect the polarization phenomenon of the battery; the model is simple to establish, and a good model can ensure the sorting accuracy.	It is difficult to fully reflect the battery polarization phenomenon in actual operation.	It is difficult to fully reflect the battery polarization phenomenon in actual operation.
Neural network algorithm	No prior knowledge and category information is required; high reliability; wide range of application.	It is easy to fall into the local optimum; the algorithm is not fully applicable and needs to be improved; the complexity is higher.	Improve the algorithm and reduce complexity.
Clustering algorithm	Can learn independently; the speed is relatively fast.	High initial parameter requirements; requires a lot of data training.	Improve the model and reduce the number of training to meet the requirements.
Statistical algorithm	The requirements on the model are not high; the speed is fast; it is easy to integrate with other methods.	Strict assumptions are required; abnormal parameters are difficult to handle.	
Electrochemical parameter analysis	Sorting, according to the battery mechanism and strong persuasion; good applicability; can be applied to large batch sorting.	Electrochemical parameters are difficult to measure; laws are difficult to find.	Try to find a simpler method for measuring electrochemical parameters; look for other electrochemical parameters.

To sum up, the future development of battery sorting methods may focus on the following three aspects: first, new instruments or technologies will be introduced to increase the capture of internal characteristics of batteries, such as computed tomography (CT) and ultrasound or X-ray, to scan images inside the batteries and achieve the purpose of screening [147,148], or use a combination of internal resistance, capacity testing, and x-ray methods to classify batteries [149]. Second, the model and algorithm of the battery will be updated and developed to make the model closer to the real polarization reaction of batteries and make the algorithm more applicable to the sorting of power batteries. Finally, battery sorting methods should be more closely associated with new technologies, such as big data and machine learning, which are popular today, to keep up with the trend of technology and times. For example, reference [150] sorts batteries using the SQL database.

6. Conclusions

This paper makes a systematic summary of the existing sorting methods of power batteries. Although a large number of sorting methods have been investigated, each method has its possibilities and deficiencies for improvement. These methods should be improved by further experiments and combined with practical engineering. Through this paper, the author expects that people involved in the battery industry can be inspired. Engineers can choose appropriate methods to sort batteries according to actual needs. Hopefully, this paper can help researchers develop more effective sorting methods. In the future, the sorting process can be developed to be more concise, effective, quick, and accurate, which requires us to make constant attempts and innovations and strive to find a more appropriate sorting method.

Author Contributions: Writing—original draft preparation, H.Z.; writing—review and editing, R.L. and H.Z.; funding acquisition, R.L.; project administration, R.L.; investigation, W.L. and X.Z.; formal analysis, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research Program of China, Grant number 2016YFC0300104, the Advanced Research Project of Equipment of China under Grant 41421040301, and the Elite Project of Harbin University of Science and Technology under Grant LGYC2018JC026.

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

References

1. Sun, G.; Chen, Y. Experimental study on the screening criteria of echelon use of returned power battery. *Chin. J. Power Sources* **2018**, *42*, 1818–1821.
2. Neupert, S.; Kowal, J. Inhomogeneities in Battery Packs. *World Electr. Veh. J.* **2018**, *9*, 20. [[CrossRef](#)]
3. Das, A.; Li, D.; Williams, D.K. Joining Technologies for Automotive Battery Systems Manufacturing. *World Electr. Veh. J.* **2018**, *9*, 22. [[CrossRef](#)]
4. Jiya, I.N.; Gurusinge, N.; Gouws, R. Combination of LiCs and EDLCs with Batteries: A New Paradigm of Hybrid Energy Storage for Application in EVs. *World Electr. Veh. J.* **2018**, *9*, 47. [[CrossRef](#)]
5. Wang, J.-Y.; Sun, Z.-C.; Wei, X.-Z.; Dai, H.-F. Research on power battery cell classification method for electric vehicles. *Chin. J. Power Sources* **2012**, *36*, 94–98.
6. Jia, F.-C.; Liu, Y. Group Scheme of Power Lithium Ion Battery. *Guangzhou Chem. Ind.* **2015**, *43*, 28–29.
7. Dong, H.; Gou, L.; Gan, Y. Research status and trend of power lithium battery cascade utilization matching research. *Metall. Autom.* **2017**, *S2*, 301–303.
8. Ma, J.; Li, A.; Du, T.; Liu, F. Research Development on the Methods of Making Sets of Lithium-ion Battery. In Proceedings of the 19th Branch of the 14th Annual Conference of the China Association for Science and Technology: The Seminar on Charge and Discharge of Electric Vehicle, Shijiazhuang, China, 18 September 2012.
9. Wang, L.; Xie, L.; Zhang, G.; He, X. Research progress in the consistency screening of Li-ion batteries. *Energy Storage Sci. Technol.* **2018**, *7*, 194–202.
10. Yang, F. Inconformity of Li Battery Pack and Remedial Measures. *Auto Electr. Parts* **2014**, *5*, 37–40.
11. An, F.; Zhang, J.; Huang, J. Production of lithium-ion battery and uniformity evolution analysis. *Trans. Mater. Heat Treat.* **2015**, *36*, 239–248.
12. Feng, J.; Guo, J.; Wang, X.-H.; Duan, B.-J. Investigation of screening method for Li-MnO₂ battery. *Chin. J. Power Sources* **2014**, *38*, 1249–1250+1275.
13. Xiao, T.; Fan, Y.-F. The design of Bluetooth battery sorting system. *Equip. Manuf. Technol.* **2017**, *3*, 172–174.
14. Yu, B. Analysis of the secondary battery detection and sorting system. *Sci. Technol. Innov. Guide* **2014**, *11*, 44.
15. Ro, H. Sorting Machine of Battery Cell and Sorting Method Thereof. U.S. Patent 9,209,496, 8 December 2015.
16. Zhou, Y. Design for formalizing and separating system of lithium battery. *J. Harbin Bearing* **2014**, *35*, 106–107.
17. Li, P. Battery AC internal resistance automatic sorting system. *J. Harbin Univ. Sci. Technol.* **1999**, *1*, 3–5.
18. Li, S.; Liu, H.; Wan, Q. Automatic sorting device for secondary battery internal resistance detection. *Users Instrum.* **2005**, *4*, 45–47.
19. Shen, J.; Qu, Y.; Li, F. A New Lithium-ion Battery Separator Based on PLC. *Electron. Sci. Technol.* **2015**, *28*, 14–17+21.

20. Yu, J.; Wen, Y.-M.; Zhan, K.-Y.; Dong, W.-H.; Kong, M.; Zeng, C.-M. Test and separation system for rechargeable battery based on network platform. *Chin. J. Power Sources* **2007**, *6*, 478–480+487.
21. Zhou, J.; Liu, S.; He, K.; Zhu, Y. Fast sorting system of battery based on FPGA. *Chin. J. Power Sources* **2014**, *38*, 1866–1868.
22. Han, W.; Zhang, W.; Wang, L.; Li, Z.-Y.; Liu, G.-Q. New technology in automobile power battery group assembly—According to method of volt-ampere characteristic curve of sorting batteries. *Chin. J. Power Sources* **2014**, *38*, 2225–2227.
23. Wang, S.; Yin, Z.; Zheng, Z.; Wang, Y.; Zou, H.; Yan, Y. A Sorting Method for Retired Battery modules Based on Voltage Curves. In Proceedings of the CSEE, Barcelona, Spain, 10–12 June 2020.
24. Li, J.; Wu, M.; Liu, Y. Research of Li-ion battery intelligent classifying system based on charge and discharge curve. *Chin. J. Power Sources* **2011**, *35*, 912–914.
25. Du, C.; Luo, D.; Zhang, C. Study on screening method of lithium ion power battery. *Chin. J. Power Sources* **2017**, *41*, 977–980.
26. Li, X.; Qi, J. Research on single battery voltage unbalance in storage battery. *Guizhou Electr. Power Technol.* **2014**, *17*, 54–55+45.
27. Zeng, Y.; Yang, Y.; He, Z. Lead-acid Battery Automatic Grouping System Based on Graph Cuts. *Electr. Power Compon. Syst.* **2016**, *44*, 450–458. [[CrossRef](#)]
28. Wang, L.; Wang, W.; Wang, Z.; Zhang, Y.; Liu, S. Study on inconsistency of lithium titanate battery in rail transportation. *Chin. J. Power Sources* **2017**, *41*, 195–197.
29. Li, Y.; Wang, Y.-W.; Zhang, H.-C.; Zhang, N. Investigation of sorting with dynamic state of charge of lithium-iron-phosphate power battery. *J. Jilin Univ.* **2011**, *41*, 331–333.
30. Kim, J.-H.; Shin, J.-W.; Jeon, C.-Y. Screening Process of Li-ion Series Battery Pack for Improved Voltage/SOC Balancing. In Proceedings of the 2010 International Power Electronics Conference, Sapporo, Japan, 21–24 June 2010.
31. Fan, M.-Q.; Liao, W.-L.; Wu, B.-R.; Chen, H.; Zhu, L.; Jian, X.-Y.; Liu, M.-Y. Study of consistency and selected method of Ni-MH battery. *Chin. J. Power Sources* **2005**, *6*, 361–364.
32. Li, X.; Wang, T.; Pei, L. A comparative study of sorting methods for lithium-ion batteries. In Proceedings of the 2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific), Beijing, China, 31 August–3 September 2014; pp. 1–6.
33. Muhammad, M.; Attidekou, P.S.; Ahmeid, M. Sorting of Spent Electric Vehicle Batteries for Second Life Application. In Proceedings of the 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 12–14 August 2019; pp. 325–329.
34. Zhou, Z.; Duan, B.; Kang, Y.; Shang, Y.; Cui, N.; Chang, L.; Zhang, C. An efficient screening method for retired lithium-ion batteries based on support vector machine. *J. Clean. Prod.* **2020**, *267*, 121882. [[CrossRef](#)]
35. Li, J.; Wang, Y.; Tan, X. Research on the Classification Method for the Secondary Uses of Retired Lithium-ion Traction Batteries. *Energy Procedia* **2017**, *105*, 2843–2849. [[CrossRef](#)]
36. Zhang, G. Research on Reliability for Commercial 18650 Lithiumion Battery. Ph.D. Thesis, Tsinghua University, Beijing, China, 2017.
37. He, X.; Zhang, G.; Feng, X.; Wang, X.; Tian, G.; Ouyang, M. A facile consistency screening approach to select cells with better performance consistency for commercial 18650 lithium ion cells. *Int. Electrochem. Sci.* **2017**, *12*, 1023–1025.
38. Zhang, W.-H.; Pei, F.; Liu, P. Electrochemical impedance analysis of LiFePO₄/C batteries in cycling process. *Chin. J. Power Sources* **2015**, *39*, 54–57.
39. Li, X.; Lan, X.; Tang, Q. Research on Uniform Sorting Method for Automotive Lithium-ion Batteries. *J. Power Supply* **2020**. Available online: <http://kns.cnki.net/kcms/detail/12.1420.TM.20191118.1000.010.html> (accessed on 18 November 2019).
40. Chen, S.; Zeng, Z. Research on the automatic assembly plan of power lithium battery. *Mech. Eng. Autom.* **2018**, *5*, 142–144.
41. Yan, Y.; Gu, Z.; Huang, H.; Lu, C. Selecting method on secondary use of power Li-ion battery. *Battery Bimon.* **2018**, *48*, 414–416.
42. Wen, C.-G.; Wang, Y.-Y.; Feng, W.-F.; Ma, W.-T. Study of separation process of Li-battery based on multivariable data fitting. *Chin. J. Power Sources* **2018**, *42*, 1480–1482.

43. Cai, M.; Chen, W.-J.; Xu, J.-B.; Tan, X.-J. Research on classification method of secondary use of retired LiFePO₄ batteries. *Chin. J. Power Sources* **2019**, *43*, 781–784.
44. Kim, J.; Shin, J.; Chun, C. Stable configuration of a Li-ion series battery pack based on a screening process for improved voly-age /SOC balancing. *IEEE Trans. Power Electron.* **2012**, *27*, 411–424. [[CrossRef](#)]
45. Xu, Y.; Yu, L.-M.; Gao, Q. Power battery combination method of electric vehicle based on capacity maximization. *Chin. J. Power Sources* **2019**, *43*, 91–94.
46. Ke, L.; Wang, Y.; Hu, Y. Safety Design of Power Bank Based on Standard. *Autom. Inf. Eng.* **2015**, *36*, 45–48.
47. Shi, J.; Li, H.; Qiu, H. Research on Emergency Energy Storage Equipment Technology for Waste Power Battery Ladder Utilization. *Automob. Appl. Technol.* **2020**, *10*, 4–7.
48. Wu, F.; Wu, S.; Pei, F. Research on the grouping and management technology of lithium iron phosphate batteries for cascade utilization. *Electr. Appl.* **2016**, *35*, 64–68.
49. Xue, H.; Tao, Y.-B.; Yang, B.; Wu, F.-B.; Sun, -L. Screening method of retired LiFePO₄ batteries based on aging mechanism analysis. *Chin. J. Power Sources* **2020**, *44*, 660–665.
50. Bai, K.; Li, N.; Fan, M. Research on the Technical Roadmap for Engineering Application of Large-Scale Echelon Use Battery Energy Storage System. *North China Electr. Power* **2017**, *3*, 39–45.
51. Li, X.-L.; Chen, Q.; Guan, Y. Test characteristic analyse of second use of lithium-ion power batteries. *Chin. J. Power Sources* **2013**, *37*, 1940–1943.
52. Qin, J. Application and Distribution of Lithium-ion Battery. *Value Eng.* **2013**, *32*, 297–299.
53. Wang, X.-W.; Guo, Z.; Zhang, G.-J.; Zhang, C.-S. Study on packing technology for different types of lithium-ion batteries. *Chin. J. Power Sources* **2014**, *38*, 1437–1439.
54. Zhang, H.; Wang, D. Auto Testing and Sorting System of the Battery's Characteristics Base on the IC Card Battery Tray. *Equip. Electron. Prod. Manuf.* **2010**, *39*, 21–24+34.
55. Liao, Y.-W. Design for Smart Distribution Group System of Battery. *J. Hubei Univ. Arts Sci.* **2009**, *30*, 20–23.
56. Guo, Z. About the lead-acid battery matching. *China Bicycl.* **2009**, *2*, 33–36.
57. Gui, C.-Q. Matched group of VRLA battery used for electric bicycle. *Battery Bimon.* **2005**, *3*, 53–54.
58. Li, N.; Bai, K.; Wang, K.-R. Performance and prediction of retired electric vehicle battery recycling in electric energy storage condition. *Chin. J. Power Sources* **2019**, *43*, 445–449.
59. Li, J.; Li, Y.; Lyu, C.; Zhao, W.; Zhou, J. Key Technology and Research Status of Cascaded Utilization in Decommissioned Power Battery. *Autom. Electr. Power Syst.* **2020**, *44*, 172–184.
60. Zhao, M.; Li, N.; Yuan, J. Evaluation Index of Consistency of Internal Resistance of Echelon-use Lithium Battery. *Sino-Glob. Energy* **2018**, *23*, 86–92.
61. Mi, J.-F.; Fan, M.-S.; Wang, H. Performance study of retired power lithium iron phosphate batteries. *Chin. J. Power Sources* **2019**, *43*, 217–220.
62. Li, Z.; Dong, H.-C. Feasibility study of secondary utilization of retired power lithium-ion battery. *Chin. J. Power Sources* **2016**, *8*, 1582–1584.
63. Duan, S.-H.; Jia, Q.-R.; Dai, B.; Liu, X.-J. Screening method for self-discharging of lithium iron phosphate Li-ion battery. *Battery Bimon.* **2015**, *2*, 44–47.
64. Yang, G.; Cui, Y.; Zhou, J. Research on the selecting methods for Li-ion cells. *Chin. Battery Ind.* **2009**, *14*, 152–154.
65. An, F.; Zhao, H.; Li, P. Self-discharge rates in cells have a critical effect on the cycle life of parallel lithium-ion batteries. *RSC Adv.* **2018**, *8*, 30802–30812. [[CrossRef](#)]
66. Liao, Q.; Mu, M.; Zhao, S. Performance assessment and classification of retired lithium ion battery from electric vehicles for energy storage. *Int. J. Hydrogen Energy* **2017**, *42*, 18817–18823. [[CrossRef](#)]
67. Chen, H.; Wu, B.-R.; Zhu, L. Selection and performance of Ni/MH power batteries. *Battery Bimon.* **2004**, *34*, 99–101.
68. You, L.-R.; Zhang, J.-G.; Wang, Y. Classification method of Ni-MH battery based on Data-Fusion theory. *Chin. J. Power Sources* **2000**, *24*, 149–152.
69. Huang, J. Consistency and sorting method of lithium-ion batteries for electric vehicles. Institute of Energy Storage Engineering of the Chemical Industry and Engineering Society of China. In Proceedings of the Abstract Collection of the First National Energy Storage Science and Technology Conference, Kanazawa, Japan, 27–31 July 2014.
70. An, F.; Huang, J.; Wang, C. Cell sorting for parallel lithium-ion battery systems: Evaluation based on an electric circuit model. *J. Energy Storage* **2016**, *6*, 195–203. [[CrossRef](#)]

71. Duo, Z.; Li, G. Study on method of battery classification with wormform recognition ability. *Chin. J. Power Sources* **1998**, *4*, 38–42.
72. Li, R.; Wu, J.; Wang, H. Classification of battery consistency based on multi-spectral method. *Chin. J. Power Sources* **2010**, *10*, 7.
73. Haiying, W.; Kai, D.; Gechen, L. Research on the consistency of the power battery based on multi-points impedance spectrum. In Proceedings of the International Forum on Strategic Technology 2010, Ulsan, Korea, 13–15 October 2010; pp. 1–4.
74. Ye, M.; Song, X.; Xiong, R. A Novel Dynamic Performance Analysis and Evaluation Model of Series-Parallel Connected Battery Pack for Electric Vehicles. *IEEE Access* **2019**, *7*, 14256–14265. [[CrossRef](#)]
75. Wang, Q.; Qi, W. Study on influence of sorting parameters to lithium-ion battery pack life-cycles based on cell consistency. *Int. J. Electr. Hybrid Veh.* **2018**, *10*, 223–235. [[CrossRef](#)]
76. Shen, J.; Tang, Y.; Li, Y. A new method based on unsupervised clustering for lithium-ion battery classification. *Comput. Appl. Chem.* **2007**, *24*, 305–308.
77. Li, X. A screening method for the consistency of lithium-ion batteries. *Today Electron.* **2018**, *3*, 52–53.
78. Li, W.; Chen, S.; Peng, X. A Comprehensive Approach for the Clustering of Similar-Performance Cells for the Design of a Lithium-Ion Battery Module for Electric Vehicles. *Engineering* **2019**, *5*, 795–802. [[CrossRef](#)]
79. Yang, H.-Y.; Chen, J.-H.; Tang, Z.-M. Screening decommissioned power batteries based on K-means algorithm and genetic algorithm. *Chin. J. Power Sources* **2019**, *43*, 2001–2004.
80. Yang, Y.; Gao, M.; He, Z. A Robust Battery Grouping Method Based on a Characteristic Distribution Model. *Energies* **2017**, *10*, 1035. [[CrossRef](#)]
81. Cai, D.; Chen, P.; Tang, W.; You, L.; Peng, T. Core Sorting of Lithium Battery based on Improved ISODATA Algorithm. In Proceedings of the 2019 Chinese Automation Congress (CAC), Hangzhou, China, 22–24 November 2019; pp. 3958–3963. [[CrossRef](#)]
82. Pallonetto, F.; Galvani, M.; Torti, A. A Framework for Analysis and Expansion of Public Charging Infrastructure under Fast Penetration of Electric Vehicles. *World Electr. Veh. J.* **2020**, *11*, 18. [[CrossRef](#)]
83. Xu, G.; Chen, H.; Gong, M. A clustering method based on cascade utilization of battery in series. *Electr. Technol.* **2017**, *1*, 37–41.
84. Li, X.; Song, K.; Wei, G.; Lu, R.; Zhu, C. A Novel Grouping Method for Lithium Iron Phosphate Batteries Based on a Fractional Joint Kalman Filter and a New Modified K-Means Clustering Algorithm. *Energies* **2015**, *8*, 7703–7728. [[CrossRef](#)]
85. Jiao, D.-S.; Kang, X.-N.; Pan, M.-Y.; Li, X.-L.; Chi, Z.-J. A consistency evaluation method for battery capacity. *Chin. J. Power Sources* **2016**, *40*, 1429–1433.
86. Yao, J.; Zhou, Y.; Li, R.; Li, S. Research on multistage sorting method of zinc silver power battery based on LS-SVM and FCM. *J. Nat. Sci. Heilongjiang Univ.* **2018**, *35*, 484–492.
87. Wang, D.; Yang, F.; Gan, L. Fuzzy Prediction of Power Lithium Ion Battery State of Function Based on the Fuzzy c-Means Clustering Algorithm. *World Electr. Veh. J.* **2019**, *10*, 1. [[CrossRef](#)]
88. Lyu, C.; Song, Y.; Wang, L. A new method for lithium-ion battery uniformity sorting based on internal criteria. *J. Energy Storage* **2019**, *25*, 100885. [[CrossRef](#)]
89. Wang, D.-M.; Feng, W.-F.; Bai, H.-Y.; Liu, Z.-Z. Research on clustering algorithm based on voltage platform for cells classification. *Chin. J. Power Sources* **2016**, *40*, 994–996+1007.
90. Rui, Z.; Yongqin, Z.; Ran, L. A battery sorting scheme based on fuzzy C-mean clustering, taking advantage of the flatness of discharge voltage curve. *Automot. Eng.* **2017**, *39*, 864.
91. Jones, B.L.; Smith, P.; Clifton, J.M. Battery Testing and Classification. U.S. Patent 6,526,361, 25 February 2003.
92. Zhi, Y.; Ran, L. Research for classification method of battery based on state of health. *Int. J. Secur. Appl.* **2016**, *10*, 47–54.
93. Xin, C.; Zhao, F.; Wu, Y. Research on automatic matching model of power battery. In *International Conference on Mechanical Design*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 749–759.
94. Fu, Y.; Quan, S. Improved fuzzy C-means clustering algorithm and application of lithium battery assembly. *J. Henan Univ. Sci. Technol.* **2017**, *38*, 43–48+118.
95. Wang, Q.; Cheng, X.Z. A new algorithm for a fast testing and sorting system applied to battery clustering. In Proceedings of the 2017 6th International Conference on Clean Electrical Power (ICCEP), Liguria, Italy, 27–29 June 2017.

96. Wang, L.; Liu, J.; Ye, Q. Sorting method of lithium-ion batteries in mass production. *IOP Conf. Ser. Earth Environ.* **2020**, *512*, 012127. [[CrossRef](#)]
97. Li, R.; Yao, J.; Zhou, Y. Study on sorting method of zinc silver battery based on multi-step FCM clustering algorithm. *IEICE Electron. Express* **2019**, *16*, 20190120. [[CrossRef](#)]
98. Li, R.; Xu, S.; Zhou, Y. Toward Group Applications of Zinc-Silver Battery: A Classification Strategy Based on PSO-LSSVM. *IEEE Access* **2020**, *8*, 4745–4753. [[CrossRef](#)]
99. Guo, L.; Liu, G.W. Research of lithium-ion battery sorting method based on fuzzy C-means algorithm. *Adv. Mater. Res. Trans. Tech. Publ.* **2012**, *354*, 983–988. [[CrossRef](#)]
100. Zhao, Y.-F.; Feng, G.-B.; Geng, B.; Liu, J.; Chen, X.-J. Research of dynamic characteristic match of lead-acid batteries. *Chin. J. Power Sources* **2007**, *10*, 808–810.
101. Yin, J.; Wang, W.; Yuan, X.; Xu, W.; Li, X.; He, Z. Study on Rapid Evaluation and Sorting Method of Cascade Lithium Battery. *J. Chongqing Univ. Technol.* **2020**, *34*, 15–23.
102. He, Z.; Gao, M.; Ma, G. Battery Grouping with Time Series Clustering Based on Affinity Propagation. *Energies* **2016**, *9*, 561. [[CrossRef](#)]
103. Xu, Z.; Wang, J.; Lund, P.D. A novel clustering algorithm for grouping and cascade utilization of retired Li-ion batteries. *J. Energy Storage* **2020**, *29*. [[CrossRef](#)]
104. Bai, X.; Tan, J.; Wang, X. Study on distributed lithium-ion power battery grouping scheme for efficiency and consistency improvement. *J. Clean. Prod.* **2019**, *233*, 429–445. [[CrossRef](#)]
105. Lee, H.; Kang, C.; Park, Y. Study on Power Management Strategy of HEV using Dynamic Programming. *World Electr. Veh. J.* **2016**, *8*, 274. [[CrossRef](#)]
106. Wu, Y.-L.; Li, G.-C.; Chen, S.-L. The Application of BP Neural Network in Battery-sorting. *J. Harbin Univ. Sci. Technol.* **2001**, *5*, 10–13.
107. He, F.; Shen, W.X.; Song, Q. Clustering LiFePO₄ cells for battery pack based on neural network in EVs. In Proceedings of the 2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific), Beijing, China, 31 August–3 September 2014.
108. Xia, B.; Yang, Y.; Zhou, J. Using Self Organizing Maps to Achieve Lithium-Ion Battery Cells Multi-Parameter Sorting Based on Principle Components Analysis. *Energies* **2019**, *12*, 2980. [[CrossRef](#)]
109. Fang, K.; Chen, S.; Mu, D. Investigation of nickel–metal hydride battery sorting based on charging thermal behavior. *J. Power Sources* **2013**, *224*, 120–124. [[CrossRef](#)]
110. Paolo, R.; Leonardo, F.; Adriano, M.; Matteo, C.; Sauro, L.; Luca, F.; Paolo, B.; Roberto, I. Selection of Lithium Cells for EV Battery Pack Using Self-Organizing Maps. *Automot. Saf. Energy Technol.* **2011**, *2*, 157–164.
111. He, F.; Shen, W.; Song, Q. Self-organising map based classification of LiFePO₄ cells for battery pack in EVs. *Int. J. Veh. Des.* **2015**, *69*, 151–167. [[CrossRef](#)]
112. Xu, Y. Capacity Estimation and Cascade Utilization Method of Retired Lithium Ion Batteries. *J. Nanoelectron. Optoelectron.* **2017**, *12*, 803–807. [[CrossRef](#)]
113. Lai, X.; Qiao, D.; Zheng, Y. A Novel Screening Method Based on a Partially Discharging Curve Using a Genetic Algorithm and Back-Propagation Model for the Cascade Utilization of Retired Lithium-Ion Batteries. *Electronics* **2018**, *7*, 399. [[CrossRef](#)]
114. Chen, Z.; Guo, N.; Li, X. Battery Pack Grouping and Capacity Improvement for Electric Vehicles Based on a Genetic Algorithm. *Energies* **2017**, *10*, 439. [[CrossRef](#)]
115. Shen, S.; Sadoughi, M.; Li, M. Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries. *Appl. Energy* **2020**. [[CrossRef](#)]
116. Shen, S.; Sadoughi, M.; Chen, X. A deep learning method for online capacity estimation of lithium-ion batteries. *J. Energy Storage* **2019**, *25*, 100817. [[CrossRef](#)]
117. Song, X.; Yang, F.; Wang, D. Combined CNN-LSTM Network for State-of-Charge Estimation of Lithium-Ion Batteries. *IEEE Access* **2019**, *7*, 88894–88902. [[CrossRef](#)]
118. Chen, C.; Xiong, R.; Yang, R. State-of-charge estimation of lithium-ion battery using an improved neural network model and extended Kalman filter. *J. Clean. Prod.* **2019**, *234*, 1153–1164. [[CrossRef](#)]
119. Choi, Y.; Ryu, S.; Park, K. Machine Learning-Based Lithium-Ion Battery Capacity Estimation Exploiting Multi-Channel Charging Profiles. *IEEE Access* **2019**, *7*, 75143–75152. [[CrossRef](#)]
120. Hong, J.; Wang, Z.; Chen, W. Synchronous multi-parameter prediction of battery systems on electric vehicles using long short-term memory networks. *Appl. Energy* **2019**, *254*, 75143–75152. [[CrossRef](#)]

121. Bian, C.; He, H.; Yang, S. Stacked bidirectional long short-term memory networks for state-of-charge estimation of lithium-ion batteries. *Energy* **2020**, *191*, 116538. [CrossRef]
122. Xu, W.; Xiao, L.; Zhu, Z. (Eds.) *Computer Engineering and Technology*; Springer: Singapore, 2019.
123. Khumprom, P.; Yodo, N. A Data-Driven Predictive Prognostic Model for Lithium-ion Batteries based on a Deep Learning Algorithm. *Energies* **2019**, *12*, 660. [CrossRef]
124. Ren, L.; Zhao, L.; Hong, S. Remaining Useful Life Prediction for Lithium-Ion Battery: A Deep Learning Approach. *IEEE Access* **2018**, 50587–50598. [CrossRef]
125. Patil, M.A.; Tagade, P.; Hariharan, K.S. A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation. *Appl. Energy* **2015**, *159*, 285–297. [CrossRef]
126. Lucian, U.; Mihai, V.; Micea, G. Online state of health prediction method for lithium-ion batteries, based on gated recurrent unit neural networks. *Int. J. Energy Res.* **2020**, *44*. [CrossRef]
127. Kim, M.; Chun, H.; Kim, J. Data-efficient parameter identification of electrochemical lithium-ion battery model using deep Bayesian harmony search. *Appl. Energy* **2019**, *254*, 113644. [CrossRef]
128. Tagade, P.; Hariharan, K.S.; Ramachandran, S. Deep Gaussian process regression for lithium-ion battery health prognosis and degradation mode diagnosis. *J. Power Sources* **2020**, *445*, 227281. [CrossRef]
129. Zhang, C.; Chen, Z. Analysis of Power Battery Pack Process Based on Statistical Model. In Proceedings of the 13th China Annual Conference on System Simulation Technology and Its Application, Huangshan, China, 3–7 August 2011.
130. Li, R.; Wu, J.; Fu, H. Lithium iron phosphate battery sorting research based on fuzzy clustering analysis. *ICIC Express Lett. Part B Appl. Int. J. Res. Surv.* **2013**, *4*, 943–949.
131. Chen, Y.-H.; Wu, W.-J.; Liu, H.-W.; Zhang, Z.-Z. Study on Sorting Technology for Lithium-ion Power Battery of Electric Vehicle. *J. Hunan Univ.* **2016**, *43*, 23–31.
132. Duo, Z.-H.; Li, G.-C.; Zhang, D.-L. A Fast Algorithm Based on Curve Recognition for Cells Classification. *J. Harbin Univ. Sci. Technol.* **2001**, *4*, 52–56.
133. Cocaña-Fernández, A.; Ranilla, J.; Gil-Pita, R. Energy-conscious fuzzy rule-based classifiers for battery operated embedded devices. In Proceedings of the 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Naples, Italy, 9–12 July 2017.
134. Cheng, D.; Chen, B.-G.; Zhang, J.-Y. Research on battery automatic sorting and grouping system. *Chin. J. Power Sources* **2018**, *42*, 981–982+1002.
135. Ye, W.-J.; Hu, Z. Study on combination method of power battery. *Chin. J. Power Sources* **2012**. Available online: http://en.cnki.com.cn/Article_en/CJFDTOTAL-DYJS201211027.htm (accessed on 29 August 2020).
136. Li, W.; Liu, S.; He, Z. Technical Difficulties Analysis of Multi-step Utilization of Power Battery. *Automob. Appl. Technol.* **2018**, *22*, 11–13.
137. Zheng, F.-D.; Jiang, J.-C.; Sun, B.-X. Study of synthesized performance evaluation method of power battery based on the target of matching battery packs. *Syst. Eng. Theory Pract.* **2015**, *35*, 528–536.
138. Liu, N.; Tang, X.; Duan, S.; Zhang, J. Capacity Optimization Method for PV-based Battery Swapping Stations Considering Second-use of Electric Vehicle Batteries. *Proc. CSEE* **2013**, *33*, 34–44.
139. Wang, X.; Gao, C.; Sun, M. Probabilistic Prediction Algorithm for Cycle Life of Energy Storage in Lithium Battery. *World Electr. Veh. J.* **2019**, *10*, 7. [CrossRef]
140. Diao, W.; Jiang, J.; Liang, H. Flexible Grouping for Enhanced Energy Utilization Efficiency in Battery Energy Storage Systems. *Energies* **2016**, *9*, 498. [CrossRef]
141. Jiang, Y.; Jiang, J.; Zhang, C.; Zhang, W.; Gao, Y.; Guo, Q. Recognition of battery aging variations for LiFePO₄ batteries in 2nd use applications combining incremental capacity analysis and statistical approaches. *J. Power Sources* **2017**, *360*, 180–188. [CrossRef]
142. Li, R.; Wu, J.F.; Wang, H.Y. Reliability assessment and failure analysis of lithium iron phosphate batteries. *Inf. Sci.* **2014**, *259*, 359–368. [CrossRef]
143. Zheng, Z.; Zhao, G.; Jin, Y.; Zhao, Z.; Gao, J. The Reutilization Screening of Retired Electric Vehicle Lithium-Ion Battery Based on Coulombic Efficiency. *Trans. China Electrotech. Soc.* **2019**, *34*, 388–395.
144. Uddin, K.; Perera, S.; Widanage, W.D. Characterising Li-ion battery degradation through the identification of perturbations in electrochemical battery models. *World Electr. Veh. J.* **2015**, *7*, 76–84. [CrossRef]
145. Podias, A.; Pfrang, A.; Persio, F.D. Sustainability Assessment of Second Use Applications of Automotive Batteries: Ageing of Li-Ion Battery Cells in Automotive and Grid-Scale Applications. *World Electr. Veh. J.* **2018**, *9*, 24. [CrossRef]

146. Chun, H.; Kim, J.; Han, S. Parameter identification of an electrochemical lithium-ion battery model with convolutional neural network. *IFAC-PapersOnLine* **2019**, *52*, 129–134. [[CrossRef](#)]
147. Ran, A.; Chen, S.; Zhang, S. A gradient screening approach for retired lithium-ion batteries based on X-ray computed tomography images. *RSC Adv.* **2020**, *10*. [[CrossRef](#)]
148. Felder, M.P.; Götze, J. State of charge classification for lithium-ion batteries using impedance based features. *Adv. Radio Sci.* **2017**, *15*, 93–97. [[CrossRef](#)]
149. Chen, H.; Shen, J. A degradation-based sorting method for lithium-ion battery reuse. *PLoS ONE* **2017**, *12*. [[CrossRef](#)] [[PubMed](#)]
150. Xu, M. Implementing Battery Consistency Function Based on SQL Database. *Mar. Electr. Electron. Eng.* **2012**, *32*, 92–95.



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