batteries

Review

Towards High-Safety Lithium-Ion Battery Diagnosis Methods

Yulong Zhang , Meng Jiang, Yuhong Zhou, Shupeng Zhao * and Yongwei Yuan

College of Mechatronical & Electrical Engineering, Hebei Agricultural University, Baoding 071001, China
* Correspondence: zhaoshupeng2023@163.com

Abstract: With the great development of new energy vehicles and power batteries, lithium-ion batteries have become predominant due to their advantages. For the battery to run safely, stably, and with high efficiency, the precise and reliable prognosis and diagnosis of possible or already occurred faults is a key factor. Based on lithium-ion batteries' aging mechanism and fault causes, this paper summarizes the general methods of fault diagnosis at a macro level. Moreover, lithium-ion battery fault diagnosis methods are classified according to the existing research. Therefore, various fault diagnosis methods based on statistical analysis, models, signal processing, knowledge and data-driven are discussed in depth. Finally, the main challenges faced by fault diagnosis technology and future directions for possible research and development are put forward.

Keywords: diagnosis; aging mechanism; lithium-ion battery

1. Introduction

In the context of the two global problems of environmental pollution and energy shortage, the new energy vehicle industry and the automotive power battery industry have been developing rapidly. Compared with other types of power batteries, including lead–acid batteries and nickel–metal hydride batteries, lithium-ion batteries have various advantages such as a high operating voltage, long cycle life, high energy density, no memory effect, and green environmental protection, and they have now become a more widely used type of power battery in the market [1,2]. However, the frequent fires and spontaneous combustion of electric vehicles have led to increasing concern about the safety of new energy vehicles. This is especially true for power batteries. There are many uncertainties in the actual use of power batteries, which is a significant aspect that triggers safety problems.

A lithium-ion battery is an energy storage and conversion device. During the charging and discharging process of the battery, a variety of chemical reactions are carried out inside it. The interaction between various substances and the mutual coupling between different reactions makes these reactions more complex, which is prone to causing battery performance degradation and faults [3,4]. In addition, under adverse conditions caused by some external factors such as mechanical, electrical, and thermal abuse, the power battery may also have faults such as deformation, leakage, and inconsistency, which may lead to safety problems [5]. Therefore, it is necessary to identify and diagnose the faults of the battery.

Fault diagnosis technology can detect and evaluate progressive faults and predict and identify sudden faults during the operation of lithium-ion batteries [6,7]. A reasonable fault diagnosis method can evaluate the health status of the battery based on external characteristics during battery operation. This has a positive effect on extending battery life, reducing battery maintenance costs, and evaluating echelon utilization. In view of the complex reaction principles and uncertain working conditions of lithium-ion batteries, suitable fault diagnosis strategies should be adopted to reduce the possibility of safety problems and ensure the efficient use of batteries. According to different principles, fault diagnosis methods can be divided into the following categories: the statistical analysis-based

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method, analytical model-based method, signal processing-based method, knowledge-based method, and data-driven method. The statistical analysis-based method is to use mathematical and statistical methods such as correlation coefficient, information entropy, and Gaussian distribution to achieve fault diagnosis. This method is simple to implement, computationally small, and generally used in conjunction with other methods [8]. However, it is easy to encounter problems such as low sensitivity and false alarms due to the reasonableness of the threshold setting. Moreover, as the number of batteries and sensor components increases, the component failure rate also increases [9]. The model-based fault method can be divided into state estimation method, parameter estimation method, and parity space method. It usually requires an accurate cell model that reflects the dynamic characteristics of the battery. Among them, the equivalent circuit model and the electrochemical model are the most applied battery models. This type of method has low data dependence and high interpretability, and it is easy to locate faults and measure the extent of faults. However, this type of method is also affected by environmental uncertainty, interference, and noise [10,11]. Signal processing-based methods often use wavelet transform and electrochemical impedance spectrum analysis. The method avoids complex model building and has better dynamic characteristics but has difficulties in dealing with early faults and fault location. It is computationally more demanding than model-based diagnostic methods [12]. The typical knowledge-based methods include expert systems, fault trees, and fuzzy logic. This method uses expert experience and historical data to build a knowledge base and inference rules that are easy to analyze qualitatively. However, it requires a specific and comprehensive understanding of battery failure. With the development of artificial intelligence technology, data-driven methods are more often used in fault diagnosis, mainly including neural networks and support vector machines. This method does not depend on a specific model and is suitable for complex and nonlinear systems, but rule building consumes time and requires a large amount of training data as support [13]. Relying on big data, the Internet of Things, digital twin, and cloud facilities are gradually entering people's vision. Combining the powerful computing and storage capabilities of the cloud platform allows for more efficient battery fault diagnosis. The article [14] applies the cloud platform to the battery internal short circuit fault diagnosis. Xiu et al. used a cloud platform to monitor the battery operation status to achieve the detection and location of abnormal battery packs [15]. The integration of the above methods to effectively identify various types of faults and achieve early warning is significant to improving the safety, reliability, and stability of the battery system in actual operation.

The purpose of this paper is to summarize the current commonly used lithium-ion battery fault diagnosis methods. The subsequent chapters are arranged as follows: the first part analyzes the aging mechanism of lithium-ion batteries and lists the common abnormal performance of lithium-ion batteries, which is the theoretical basis for lithium-ion fault diagnosis. The second part classifies and discusses different fault diagnosis methods in-depth and summarizes the characteristics of various methods through research of the literature. Finally, conclusions are drawn, a few remaining problems are presented for the current state of fault diagnosis technology, and a new idea based on cloud facilities is proposed.

2. Lithium-Ion Battery Fault Sources

Research on the safety of lithium-ion batteries began as early as the end of the last century [16]. However, due to the fledgling battery technology and limited application areas at that time, the research on battery safety performance lacked sufficient discussion of the root causes and processes of faults. Only after entering the 21st century did the discussion of aging and fault mechanisms for Li-ion batteries gradually develop and form a more mature theoretical system [17,18]. Analyzing and understanding the causes, fault modes of lithium-ion battery performance degradation can provide the basis for fault identification and diagnosis. This is an indispensable and important part of the development of fault diagnosis technology.

2.1. Lithium-Ion Battery Aging Mechanism

Early scholars have made remarkable achievements in studying the battery aging mechanism. For example, Vetter et al. [19] reviewed the aging mechanism of existing lithium-ion batteries in 2005. They discussed the causes of battery aging comprehensively from the possible decline mechanisms of positive and negative electrodes, which provided an informative reference for later studies of aging mechanisms. Ideally, only electrochemical reactions such as lithium-ion detachment and embedding in the positive and negative materials and lithium-ion migration in the electrolyte occur inside the battery. It can be assumed that no other side reactions are generated, and there is no loss of active materials or Li-ions. In the actual use of the battery, the internal reaction process of the battery is not stable due to the influence of material properties, production process, ambient temperature, charge/discharge rate, depth of discharge, and other stress conditions. The changes in the macroscopic characteristics of the battery are variations in voltage, power, internal resistance, capacity, and other performance indicators.

The aging of lithium-ion batteries during actual use includes two types, namely calendar aging and cycle aging. Calendar aging refers to the phenomenon that the capacity of the battery slowly decreases with the increase of rest time. In the process of battery rest, the dominant aging factor is the loss of lithium-ion inventory (LLI) caused by the slow thickening of the negative solid electrolyte interface (SEI) film, which is mainly affected by factors such as battery state of charge (SOC) and ambient temperature. In general, the higher the shelving SOC and the higher the storage temperature, the faster the battery calendar aging will be. Cycle aging refers to the irreversible capacity loss of Li-ion batteries during charge/discharge cycles, which is mainly affected by factors such as charge/discharge current, cut-off voltage, operating SOC interval, ambient temperature, and depth of discharge.

As shown in Figure 1, the factors affecting battery aging involve the whole life cycle process of the battery, including the design, production, and application of the battery [20]. External battery operating stresses such as voltage, current, and temperature directly accelerate the battery aging side effects. Aging modes mainly include the loss of lithium-ion inventory (LLI), loss of anode/cathode active material (LAM), and loss of electrolytes. The macroscopic performance of the battery is manifested as capacity decay and power decay, and the growth of internal resistance is generally used to characterize power decay. Studies show that the battery aging mechanism is mainly due to side reactions in the electrodes and electrolyte and their boundaries [21,22]. At the negative electrode, the SEI film is formed on the electrode surface by the reductive decomposition reaction between the electrolyte and graphite. The volume expansion during lithium-ion embedding in the negative electrode generates mechanical stresses that lead to the destruction of the SEI film. The electrolyte and electrode then form a new SEI film resulting in the thickening of the film. This will increase the internal resistance and also cause irreversible loss of active lithium ions to degrade the battery capacity [23]. Under extreme conditions, such as high multiplier charging and low-temperature charging, lithium ions will be enriched on the negative electrode surface. This can induce lithium dendrites and puncture the diaphragm, thus causing a micro/internal short circuit and the potential for sudden faults of thermal runaway [24]. At the positive electrode, loss of active electrode material or structural damage can also lead to battery capacity decay and increased internal resistance [8]. In addition, electrolyte decomposition, graphite particle flaking, collector corrosion, and adhesive decomposition can also cause loss of active material [25,26]. These aging reactions will lead to battery faults and degraded performance.

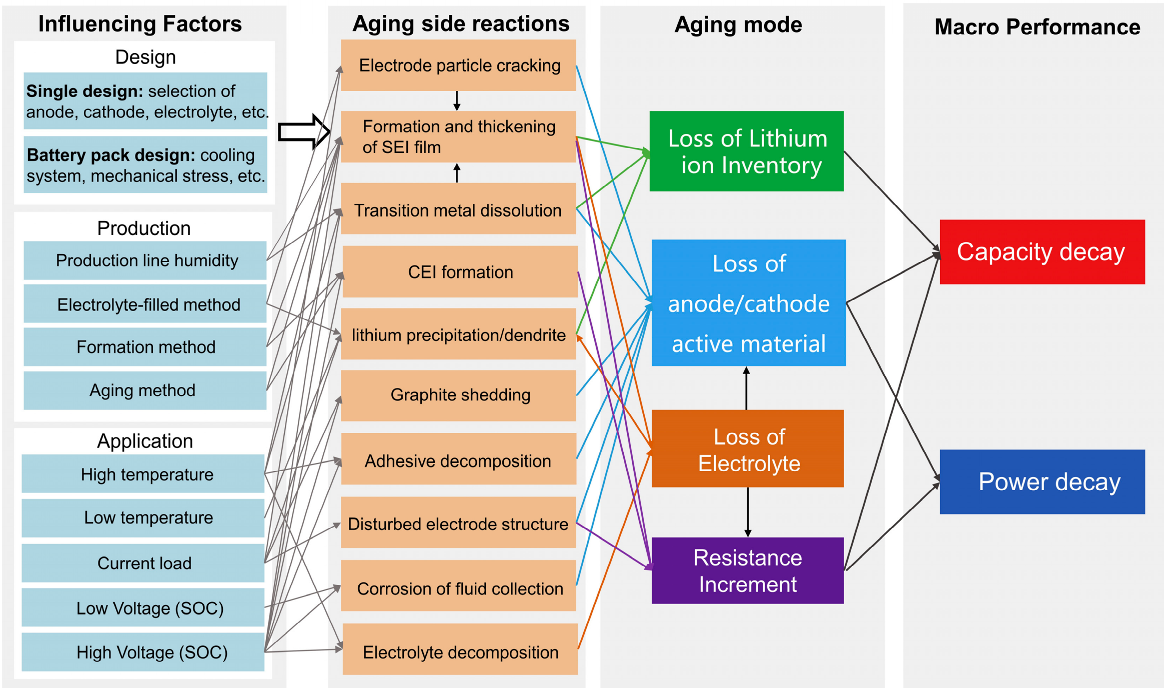

Figure 1. The aging model of lithium ion battery [27].

2.2. Common Abnormalities of Lithium-Ion Batteries

For lithium-ion battery systems, there are many other components in addition to the battery unit, such as connection components, sensors, and battery management systems (BMS). When identifying and diagnosing faults, these system-level faults should first be eliminated. Then diagnose the battery itself based on the appropriate method, and determine whether the battery itself is abnormal, which can make the solution to the problem clearer and more understandable. As shown in Table 1, most of the abnormal patterns of Li-ion batteries can be reflected by the differences and changes in various parameters. The causes of abnormalities are related to the battery manufacturing process, charge and discharge control, the occurrence of internal short circuits and chemical reactions, and the presence of various abuse situations.

Table 1. The common faults of lithium-ion batteries.

Fault Mode	Fault Performance	Fault Cause
Internal short-circuit	High temperature and fast change rate	Thermal, mechanical, and electrical abuse
High self-discharge	Low charging voltage and slow rise rate	Internal micro-short circuit or spontaneous chemical reaction
Consistency abnormalities	Significant differences in charge/discharge voltage, capacity, internal resistance, temperature, and other parameters between single cells	Poor manufacturing and grouping process, abuse
overcharge	High charging voltage, bulging, leakage, etc.	Unreasonable charge control
Over-discharge	Low discharge voltage	Control system malfunction
Liquid leakage or poor air tightness	Electrolyte leakage or bulge	Poor manufacturing process

3. Lithium-Ion Battery Fault Diagnosis Method

Fault diagnosis refers to the judgment of faults that occur or may occur in a system to clarify whether a fault has occurred, as well as the location, type, and time of occurrence. Fault diagnosis mainly includes three processes: fault detection, fault isolation, and fault identification. Fault detection is the basis for verifying the existence of a fault in the system and determining the timing of the fault; fault isolation determines the location of the fault; fault identification determines the type, status, and severity of the fault, etc.

There are various fault diagnosis methods for lithium-ion batteries, and their classification can be traced back to the 1990s, when Frank, an American scholar, outlined the traditional fault diagnosis methods [28]. With the development of science and technology, the application and research of fault diagnosis have become more extensive and in-depth. Fault diagnosis methods can be classified into the following four categories: the statistical analysis-based method, analytical model-based method, signal processing-based method, knowledge-based method, and data-driven method.

3.1. Statistical Analysis-Based Method

The statistical analysis method is a method of mathematical discipline that forms conclusions by mathematical statistics and analysis of various data and information obtained. In the battery system, the current, voltage, temperature, internal resistance, and other information of the battery are collected by various sensors. The collected data are directly analyzed by using statistical methods such as information entropy [29–31], Gaussian distribution [32,33], correlation coefficient [34,35], and maximum likelihood [36]. Moreover, fault diagnosis can be achieved by setting reasonable thresholds. Among them, the process of using the correlation coefficient to determine whether a fault occurs is shown in Figure 2a.

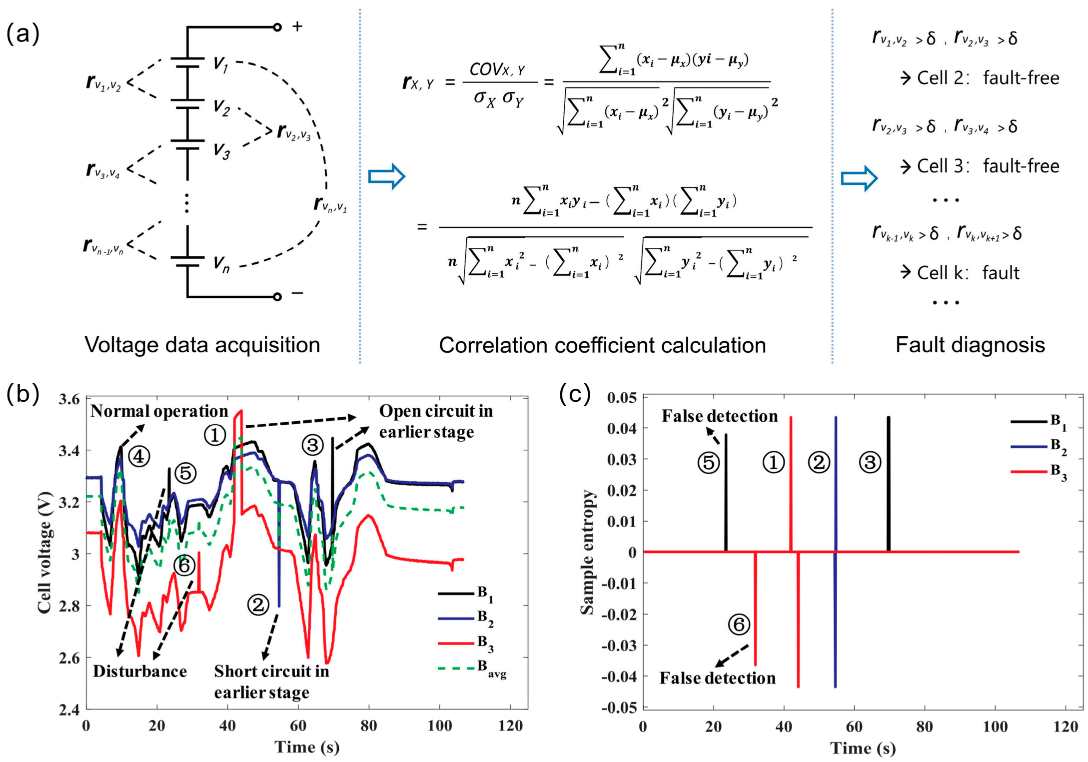

Figure 2. Static-based diagnosis (**a**) correlation-based diagnosis flow chart, (**b**,**c**) sample entropy-based diagnosis voltage raw data, and sample entropy calculation results [30,37].

The statistical analysis-based method is characterized by low computational complexity and high execution efficiency. The short-circuit fault detection method is based on the voltage curve correlation coefficient proposed in the article [37]. It directly uses the voltage measurements of the battery pack to obtain the voltage curve correlation coefficients and expresses the correlation coefficients in a recursive form. The initial stage of the short circuit is detected by capturing the cut-off voltage drop, while the latest voltage trend of the battery is maintained by using a moving average window to ensure the sensitivity of detection of short circuit faults. The detection method in the paper by comparing measured values with anomaly coefficients does not require any additional hardware or modeling effort. The method can provide robust short-circuit detection regardless of inconsistencies within the battery pack. The statistical analysis method is highly flexible in combining with other methods or models [37].

Zhang et al. proposed a real-time battery early multi-fault diagnosis method based on the modified sample entropy. The voltage data of the battery is first collected, and then the modified sample entropy of the battery voltage sequence in the detection moving window is calculated, as shown in Figure 2b,c. This diagnostic method can diagnose and predict different early battery faults, including short-circuit and open-circuit faults, and also predict the time of fault occurrence. The method has high robustness, high reliability, and low computational cost and does not require an exact model [30]. Zhenpo Wang et al. used sample entropy and Shannon entropy to perform a fault diagnosis on the voltage data from the national new energy vehicle monitoring platform. The method was able to accurately predict the time and location of voltage faults within the battery pack and concluded that Shannon entropy was more accurate in identifying voltage fluctuations [38]. In addition, the multiscale entropy method can effectively extract the multiscale features of complex signals at the early stage of battery faults and can effectively detect and locate multiple battery faults/anomalies before triggering the alarm threshold [29].

3.2. Analytic Model-Based Method

The analytic model-based method of the battery starts with the establishment of an accurate battery model. Then the model is used to obtain the parameters carrying fault information to determine whether the system is faulty. The models that can be used in current research are electrochemical models [39,40], equivalent circuit models [41,42], fractional order models [43,44], and various coupled models [45,46]. The electrochemical models can reflect the changes of various parameters inside the battery, and they can also be combined with the side reaction equations related to battery aging to investigate the aging mechanism of the battery. However, for the fault diagnosis of Li-ion batteries, the electrochemical models with many parameters and established partial differential and algebraic equations are too complicated to be suitable for practical applications. The equivalent circuit model, on the other hand, is the most widely used model with better overall evaluation in terms of complexity and computational accuracy. On this basis, the analytical model-based method can be divided into three types: the state estimation method, the parameter estimation method, and the parity space method. The diagnosis process is shown in Figure 3.

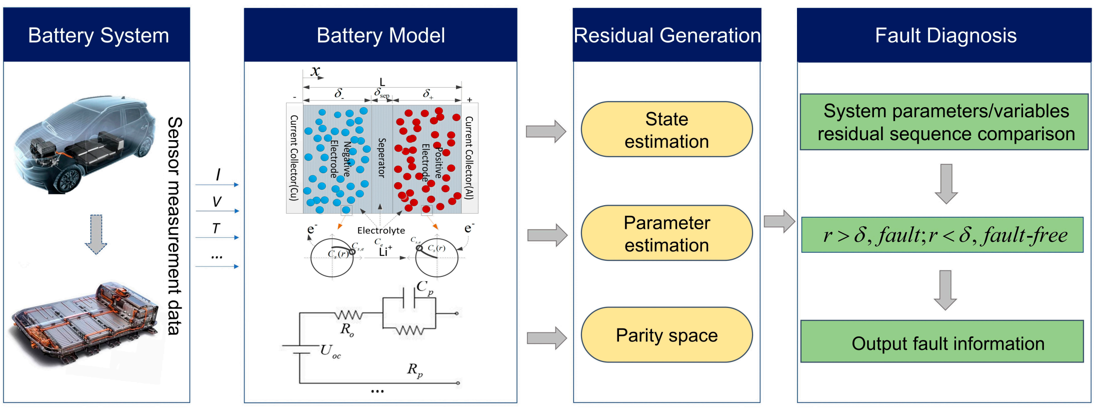

Figure 3. Model-based diagnosis.

3.2.1. State Estimation Method

The state estimation method is a mathematical model that uses filters or observers to extract fault characteristic parameters when the system is observable or partially observable. Such as the extended Kalman filter [47,48], the Unscented Kalman filter [49,50], and the Luenberger observer [44] are more commonly used algorithms. After reconstructing the measured signal into a new measurable variable with the help of a mathematical model, the estimated value is compared with the true value to generate a residual sequence. The residual signal is then compared with a given threshold value or according to the corresponding evaluation rules to determine the system fault. The key technique of the state estimation method is to reconstruct the battery system state using filters and observers. It has good real-time performance and does not require a large amount of data input, but it is difficult to determine the location and degree of fault. Thermal faults have always been one of the most critical faults in Li-ion batteries. The heat generated during battery operation is highly dependent on the internal resistance of the battery. So Wei et al. [51] used a Lyapunov-based electrical state observer to monitor battery open circuit voltage (OCV) and the internal resistance based on an electro-thermal coupling model describing the dynamic behavior of the battery charge heat. A Kalman filter-based observer is also used to estimate the dynamic changes of the cell surface temperature, thus establishing a fault diagnosis scheme with adaptive thresholds. It is finally verified that this scheme can well suppress the modeling and measurement uncertainties and effectively detect thermal faults in cylindrical Li-ion batteries.

State estimation methods can make comprehensive use of the structural, functional, and behavioral properties of battery systems if an exact mathematical model can be established. It can detect sudden faults in real-time and does not require a strict continuous excitation signal, which is the most direct and effective diagnosis method. However, as a typical nonlinear system, it is difficult to establish an accurate mathematical model for lithium-ion batteries, which is one of the bottlenecks limiting the development of this method.

3.2.2. Parameter Estimation Method

When a battery system malfunctions, the parameters reflecting its physical characteristics must have abnormal changes. The parameter estimation method is used to identify the relevant parameters and analyze their variation characteristics. Then, compare them with the parameter values during normal operation of the system and determine whether there is a fault based on the difference between the two. The parameter estimation method has advantages in fault separation and fault-tolerant control but requires accurate modeling and adequate input excitations. The parameter estimation method can also be combined with some state estimation methods to diagnose nonlinear systems to obtain better diagnostic results. Parameter estimation methods such as recursive least squares [52,53], particle filtering [54,55], and genetic algorithms [56,57] are more commonly used in nonlinear systems. In the fault diagnosis and prediction method proposed in the article [58], the least squares method with the forgetting factor was used to adjust the Lebesgue state length optimally. This led to the establishment of an online model parameter adaptive scheme combined with the particle filtering-based algorithm to improve the accuracy of battery capacity estimation and remaining service life prediction [58]. Occasional spontaneous internal short circuits in Li-ion batteries during use are a common problem. To ensure operational safety, the paper [59] proposes a scheme combining parameter estimation and state estimation methods. Based on measured voltage and temperature, it leads to the diagnosis of battery short circuits by the identification of SOC and the internal resistance of abnormal heat generation, which characterize the excessive capacity loss of each individual battery cell. Pan et al. [60] used the recursive least squares method for the online locking of faulty cells when studying the problem of internal short circuit detection in lithium-ion batteries. Hence, an accurate determination of whether an internal short circuit has occurred is achieved based on the circuit model topology.

3.2.3. Parity Space Method

The parity space method was proposed by Chow and Willsky in the early 1980s [61]. In essence, fault diagnosis separation is achieved by comparing the differences in redundancy relationships between the input and output signals in the actual system and the mathematical model [5,62]. For lithium-ion battery systems, there are three most fundamental measurements: voltage, current, and temperature. The internal consistency between these three measurements has an analytic redundancy relationship whereby dynamic equations can be established and residual vectors generated. When a fault occurs in the system, the above consistency relationship is broken and reflected in the residuals generated by the dynamic equations, thus enabling the detection of the fault. The parity space method involves only the problem of solving linear equations or linear optimization in the application process. Its structure of constructing residuals is clear and informative, which has been applied in the field of automotive fault diagnosis in recent years [63]. However, the method has limited usefulness in nonlinear systems [64], and its accuracy needs to be considered when the battery is in complex, unstable operating conditions.

3.3. Signal Processing-Based Method

Processing the raw signal is an important step in fault diagnosis. For simple target signals, the signal processing-based method can be understood as setting a threshold value, and if the target signal exceeds this threshold, the battery will be diagnosed with a fault [65]. The fault may be related to the amplitude, phase, frequency, etc., of the output signal for complex targets that are not easily detected. In this case, features can be extracted by analyzing the target signal to obtain objective laws. Finally, fault diagnosis can be achieved by judging the correlation between signal feature values and specific faults. This kind of method does not require the establishment of an accurate battery model. Wavelet transform and impedance spectroscopy analysis are both commonly used methods.

Wavelet transform has a strong suppression ability for noise. It can decompose the signal by a low-pass or high-pass filter to obtain detailed information in different frequency ranges and effectively detect whether the signal is abruptly changed so as to determine whether the fault occurs. In the actual operation of electric vehicles, the fault of batteries has complexity due to multiple factors such as electromagnetic interference, road conditions, and driving habits. Among them, the unexpected detection of noisy voltage signals may lead to misjudgment of faults. Yao et al. [66] proposed a new noise removal technique based on wavelet transform for eliminating the noise of the actual voltage values, as shown in Figure 4a. Based on the voltage signal in the non-vibration state of the battery system, the voltage signal in the vibration state is decomposed and reconstructed using discrete wavelets. Eliminate electromagnetic interference and instrument accuracy errors without distorting the voltage characteristics. Such targeted processing of the characteristic signal reduces the difficulty of fault identification caused by the nonlinear and multi-parameter coupling of the battery system. Battery external connection faults can also be detected by analyzing the correlation between each parameter and the fault signal. This method not only detects and locates battery faults but also reflects the severity of faults according to the degree of curve fluctuation. It is also feasible to use this method for many other fault identification systems based on voltage signals. In addition, the data processing performance of wavelet transform can be combined with the pattern recognition performance of the neural network by taking advantage of wavelet decomposition in data noise reduction and feature vector extraction. This can solve the problem of large data volume and data redundancy in battery systems [67], as shown in Figure 4b.

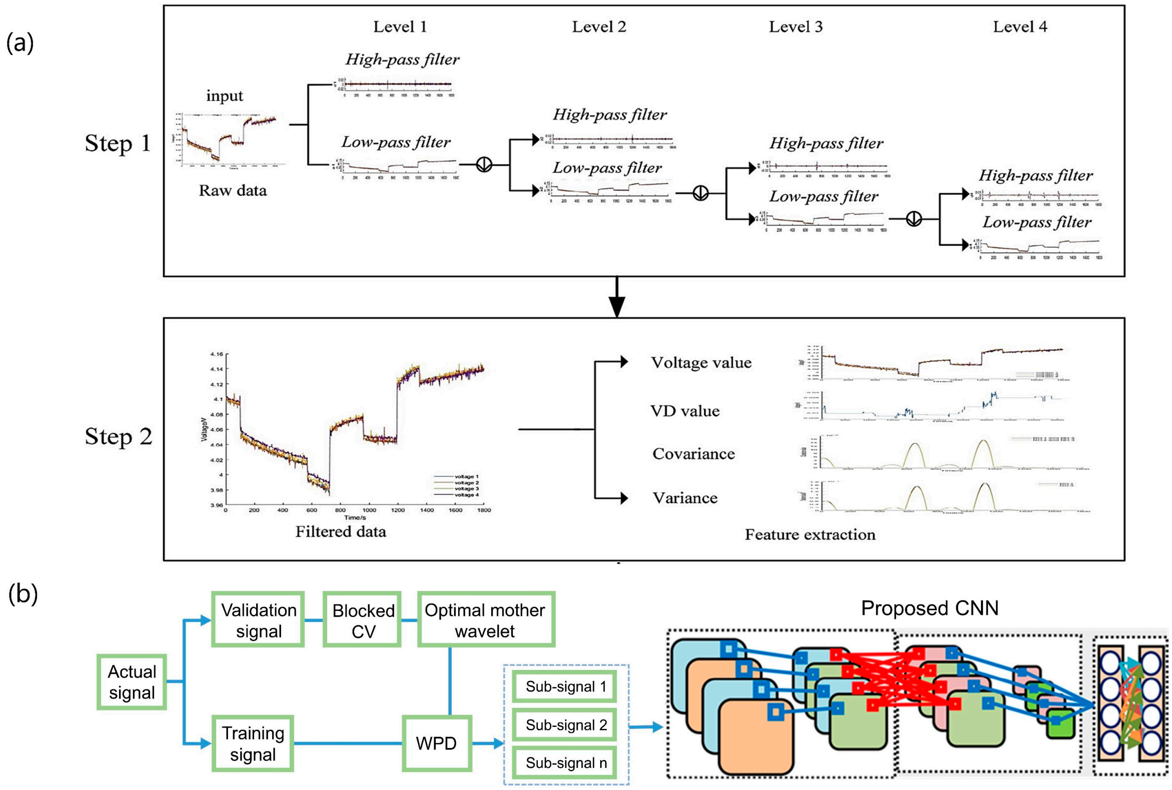

Figure 4. Wavelet transform method: (**a**) wavelet decomposition signal processing, (**b**) diagnosis based on wavelet packet decomposition and two-dimensional convolutional neural network [66,67].

Electrochemical impedance spectroscopy (EIS) is a real-time, noninvasive, and information-rich measurement method that can provide rich electrochemical information on battery aging mechanisms. In the article [68], the authors collected EIS spectra of more than 20,000 commercial Li-ion batteries as a key indicator of battery state of health (SOH) and can be used to predict the remaining useful life (RUL). The method proposed in the paper allows for estimating the capacity and RUL of a battery cycled at three constant temperatures from a single impedance measurement with simplicity and dynamic performance [68]. EIS analysis requires special equipment, such as an electrochemical station, which is one of the reasons limiting the online use of the method. However, the literature [69] proposed a circuit to perform electrochemical impedance measurements online, as shown in Figure 5a. The key is to apply a broadband current signal excitation on the cell, and the authors used a pseudo-random binary sequence to excite the cell. The clustering analysis of the measured electrochemical impedances (represented in the Nyquist diagram) in different rectangular areas associated with the actual SOH is shown in Figure 5b–d. The experimental results show that cells with different SOH cause significant changes in the electrochemical impedance, allowing the identification of frequency points at this point, and these particular frequencies can be used as a reference for cluster separation.

3.4. Knowledge-Based Method

The knowledge-based method has an early start and wide application in battery fault diagnosis. It relies mainly on subjective analysis methods, such as inferential analysis and logical judgment, to diagnose using knowledge of concepts and processing methods. This method does not require an exact mathematical model and is suitable for nonlinear and complex systems. However, it requires an in-depth study of the fault mechanism and knowledge acquisition of lithium batteries. Knowledge-based methods specifically include the expert system method [70], the graph theory method [71], and the fuzzy logic method [72]. The expert system is a computer program used to simulate the reasoning decisions of human experts. The key is to build a systematic knowledge base and reasoning mechanism using historical data and expert experience. This method is easy to understand but has limitations in learning and self-adaptive capabilities. The systematic knowledge base is also difficult to obtain. The graph theory method mainly includes signed directed graph, fault tree and failure mode and effects analysis [73]. This method is easy to analyze qualitatively and interpret diagnosis results. However, it requires a comprehensive understanding of battery fault and is not applicable to highly complex systems. The fuzzy logic method is suitable for dealing with qualitative knowledge and reasoning. It does not have the ability for self-learning and has difficulty in making effective rules. In this paper, the more typical fault tree analysis method and fuzzy logic method are selected for specific analysis.

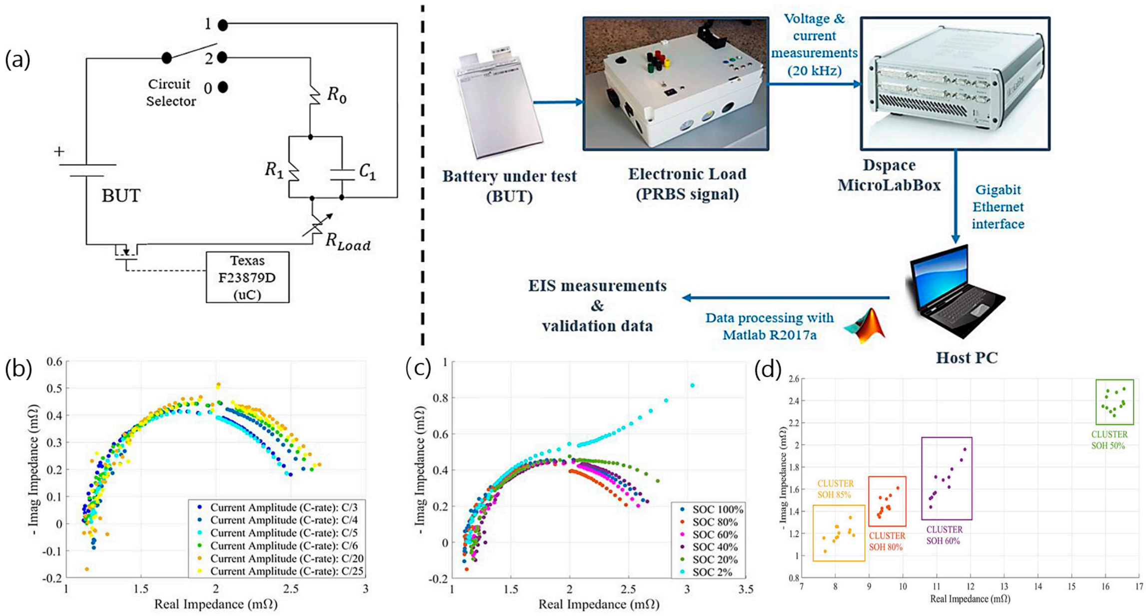

Figure 5. EIS method: (**a**) online and lab EIS measurement, (**b**,**c**) EIS Nyquist plot under different conditions, (**d**) battery EIS measurement data clustering analysis [69].

3.4.1. Fault Tree Analysis

Fault tree analysis is a deductive analysis method that models the path leading to a fault, branching down from a single point and using logical symbols to show the state of the system. A starting point is typically a fault event, then parsing downward shows why the event occurred and records the logical relationships between events. The fault tree analysis method has clear cause–effect relationships, is simpler and more effective, and is widely used in fault diagnosis. However, it is less capable of handling complex systems when more steps are required to write into the fault tree. In the article [74], the safety mechanisms of the power battery, charging pile, and power supply equipment are analyzed for the safety hazards of the electric vehicle charging process, and a fault tree for multilevel equipment integration online fault diagnosis is established. Among them, the battery fault determination module contains SOC monitoring, SOH estimation, and thermal runaway prediction, which effectively improves its safety and stability. The literature [75] proposed a battery system fault tree based on remote monitoring containing 19 faults, such as temperature difference, a high-temperature alarm, an excessive temperature rise rate, an excessive current, the sudden SOC change, and an excessive voltage polarity.

3.4.2. Fuzzy Logic

The method of fuzzy logic is to express the residuals as a fuzzy set and then use fuzzy rules for reasoning. It usually constructs the relationship between fault causes and fault phenomena and uses the membership functions and fuzzy relationship equations to solve the problem of fault cause and state identification. The fuzzy logic method is fault-tolerant and easy to implement but has poor learning ability and is weak in knowledge acquisition. Wu et al. [76] used fuzzy logic to perform a comprehensive analysis of various fault characteristics of Li-ion batteries. Its diagnostic system was established based on the connection between external characteristics and internal chemical mechanisms to achieve the diagnosis of Li-ion battery faults such as overheating, low temperature, overcharge, and over-discharge. Zheng et al. used charging data to estimate the battery capacity, the Kalman filter to perform temperature correction on the capacity estimation result, and fuzzy logic to control the observation noise, thus improving the battery life prediction accuracy [77]. Li-ion battery is a complex nonlinear system with interactions between individual fault signs. If fuzzy mathematics is applied in combination with other schemes, such as Bayesian networks, it can transform the input data into the form of affiliation of fault signs under fuzzy rules, which simplifies the diagnosis rules and reduces the uncertainty of diagnosis [78].

3.5. Data-Driven Method

With the development of machine learning and artificial intelligence, data-driven methods are gradually applied to battery fault diagnosis. The method does not rely on specific mathematical models and expert experience and can directly analyze and process the operational data of the system for fault diagnosis and separation. Its essence is to collate the fault rules of the system for diagnosis through a large amount of historical data. The fault assessment of the system mainly depends on the accuracy and amount of historical data. Although the training process or the establishment of rules is time-consuming, this type of method overcomes the requirement of a large computational volume of accurate models. It has the characteristics of artificial intelligence and is suitable for complex nonlinear systems. The knowledge-based and data-driven fault diagnosis methods are shown in Figure 6. In this paper, neural networks and support vector machines are used as examples to analyze the data-driven method.

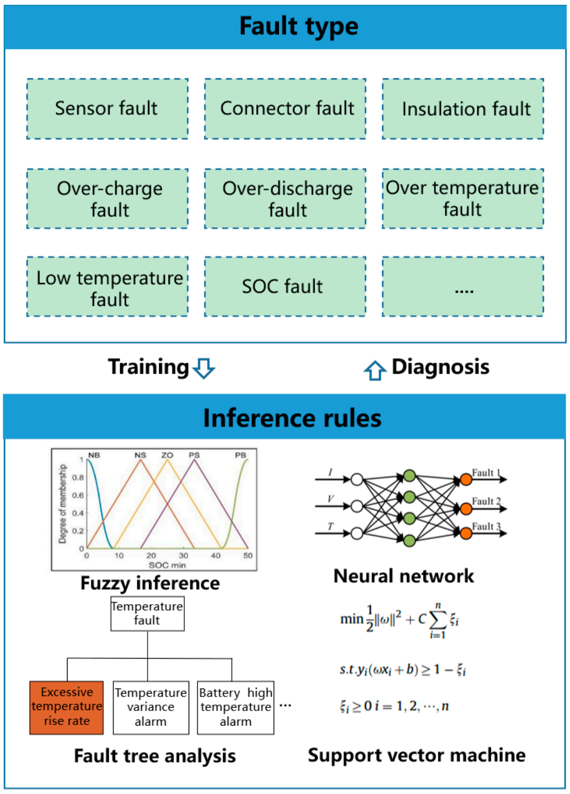

Figure 6. Knowledge-based and data-driven fault diagnosis [5,75,77,79].

3.5.1. Neural Network

Methods using neural networks usually take collected data as input and fault causes as output, rely on the acquisition of large amounts of training data, ignore the actual physical form of the diagnosed object, and have wider confidence intervals. In the article [80], a big data-based fault diagnosis method for battery systems is proposed using the data collected from Beijing Electric Vehicle Monitoring Service Center as the training and operation objects. According to the 3σ multilevel screening strategy, the abnormal changes in battery terminal voltage in the battery pack can be detected and calculated in the form of probability. Neural network algorithms are applied to combine fault and defect diagnosis results with statistical laws of big data to construct a more complete fault diagnosis model for battery systems and verify the validity of the model using the local outlier factor (LOF) algorithm. With the development of deep learning, its application in the field of fault diagnosis is also becoming widespread. Zhang et al. [81] built a deep learning model using recurrent neural networks (RNN) and long short-term memory (LSTM), which considered variable input dimensions and adaptive time series to achieve multi-step ahead prediction and long-term SOH estimation. In addition, some intelligent algorithms, such as extreme learning machines [82,83] and various neural network classifiers [84], have been applied to battery fault diagnosis.

3.5.2. Support Vector Machine

Support vector machine is a class of generalized linear classification methods that perform the binary classification of data in a supervised learning manner. Faulty data are separated from normal data by building support vectors. A support vector machine treats battery a fault diagnosis as a sample classification problem. It aims to train an accurate classifier based on historical data. Compared with neural networks, support vector machines have better generalization ability and are more suitable for small samples. In a method proposed by Feng et al. [85] for the online estimation of the state of charge of Li-ion batteries, a predictive diagnostic model based on a support vector machine was used. The support vector reflecting the intrinsic characteristics of the Li-ion battery can be determined from the battery charge data. Moreover, once the identified support vector is available, the support vector machine coefficients of cells with different signal-to-noise ratios can be identified. Then use this as a basis to compare partial charging curves and stored support vectors of fresh batteries to achieve a fast on-board diagnosis of battery SOH finally. The article [79] proposed an intelligent fault diagnosis scheme for Li-ion batteries based on a support vector machine. The scheme further proposes a grid search method to optimize the kernel function parameter and penalty factor in order to ensure the accuracy and robustness of the support vector machine, which can identify the fault state and degree of Li-ion battery more timely and effectively.

4. Conclusions and Perspectives

In this paper, fault diagnosis methods for batteries are reviewed, and their characteristics are categorized. Statistical analysis-based methods appear to be solving mathematical problems with efficient execution; analytical model-based methods are best when accurate battery models can be built and sufficient arithmetic power is available; signal processing-based methods are more suitable for nonlinear systems; and knowledge-based and data-driven methods can be applied when rich historical data are available as a basis. Of course, cross-fertilization of the above methods will certainly give better results. Although various fault diagnosis methods for lithium-ion batteries are being optimized and deepened, there are still some problems in the practical application:

1. The extraction of system parameters requires high computational power, especially when the accuracy and efficiency of the computation of complex models need to be improved. Moreover, most of the fault diagnosis research at this stage is aimed at a single fault mode, lacking a comprehensive study of multiple fault modes. Therefore, it is necessary to strengthen the research on the overall framework design of fault diagnosis systems in

order to enhance the adaptability in practical application situations. Firstly, we need to implement stratification based on the clarification of various types of fault mechanisms to set the fault diagnosis sequence reasonably. Secondly, for large-scale battery pack systems, reasonable simplification strategies need to be studied at three levels: cell, module, and system. Thus, the calculation volume of the fault diagnosis method is reduced, and the efficient operation of the fault diagnosis system is ensured.

2. The multiple causes of the same fault and the coupling between different faults are not fully understood. Most of the existing studies are mostly focused on fault detection but lack research on the causes of fault initiation. Therefore, based on the recognition of various types of fault initiation mechanisms and multiple faults coupling relationships, it is necessary to achieve a certain degree of decoupling of fault types and initiation causes. On the one hand, it helps to take protective measures at the source to avoid faults or to protect against potential faults in advance. On the other hand, it needs to be combined with the development of fault isolation and fault degree assessment methods to achieve a deep diagnosis of the fault initiation mechanism finally.

3. During the aging process of the battery, its own performance is dynamically changing, and the setting of the fault threshold needs high accuracy and adaptability. At present, it is also complicated to analyze the major components of SEI film, the location and amount of lithium plating, and the mechanism of cell expansion. So this makes it difficult to study the battery aging mechanism and design targeted thermal runaway detection and warning methods.

4. Lithium-ion battery data in more and more different application scenarios have the characteristics of multiple sources and fragmentation, which makes it more difficult to collect real-time and accurate information and condition the monitoring of the battery. In the context of the big data era, the "cloud facility" provides a new way of solving this problem. Applying the integrated end-edge-cloud technology in fault diagnosis realizes the mapping between the physical entity and the digital twin of the battery. Developing advanced sensor technology obtains the data image information on the vehicle end, such as pressure, strain, and gas. Furthermore, it is crucial to develop a smart battery with embedded sensors. Stable and fast computing can be provided through IoT technology, and data can be efficiently transferred to cloud servers. Cloud computing and storage functions are used for historical data mining and complex model calculation. Meanwhile, combining vehicle end computing alleviates the load of IoT transmission communication and cloud computing. At present, big data analysis technology has been partially applied in power battery system fault diagnosis, safety risk warning, and decline analysis and prediction. However, due to the constraints of sparse data, the coupling of feature parameters, and the strong nonlinear characteristics of power batteries, realizing end-edge-cloud fault diagnosis technology under big data to ensure efficient and stable operation of electric vehicles is still one of the challenges to be solved for power batteries.

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