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Review

A Review on the Fault and Defect Diagnosis of Lithium-Ion Battery for Electric Vehicles

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Abstract: The battery system, as the core energy storage device of new energy vehicles, faces increasing safety issues and threats. An accurate and robust fault diagnosis technique is crucial to guarantee the safe, reliable, and robust operation of lithium-ion batteries. However, in battery systems, various faults are difficult to diagnose and isolate due to their similar features and internal coupling relationships. In this paper, the current research of advanced battery system fault diagnosis technology is reviewed. Firstly, the existing types of battery faults are introduced in detail, where cell faults include progressive and sudden faults, and system faults include a sensor, management system, and connection component faults. Then, the fault mechanisms are described, including overcharge, overdischarge, overheat, overcool, large rate charge and discharge, and inconsistency. The existing fault diagnosis methods are divided into four main types. The current research and development of model-based, data-driven, knowledge-based, and statistical analysis-based methods for fault diagnosis are summarized. Finally, the future development trend of battery fault diagnosis technology is prospected. This paper provides a comprehensive insight into the fault and defect diagnosis of lithium-ion batteries for electric vehicles, aiming to promote the further development of new energy vehicles.

Keywords: electric vehicles; lithium-ion batteries; battery faults; fault diagnosis methods

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1. Introduction

Lithium-ion batteries have attracted widespread attention from both academia and industry due to their high power and energy density, long cycle life, and low self-discharge rate, which have been applied in different scenarios such as consumer electronics, electric vehicles, distributed energy storage, and large-scale energy storage [1,2]. However, as a typical energy storage device, which involves complex electrochemical reaction mechanisms, lithium-ion batteries inherently have high safety risks, having potential safety issues that can threaten reliable vehicle operation [3–5]. Theories and techniques of system engineering are demanded to pay attention to battery material system development, battery management system (BMS) design, energy storage system structure optimization, and other levels to ensure its safety and stability in actual utilization in electric vehicles [6].

Limited by the current development level of electrical, thermal, and safety management system technologies, lithium-ion batteries will suffer from mechanical, electrical, and thermal abuse during actual operation, such as overcharge, overdischarge, and overheating [7,8]. These abuses can cause a rapid degradation in battery performances and even cause internal short circuits that can lead to severe safety problems [9]. In electric vehicles, distributed energy storage, and large-scale energy storage, a large number of individual lithium batteries tend to be connected in series and parallel to form battery modules and packs to meet the demand of current, voltage, power, and energy. The large number of connected components greatly increases the complexity of the system and will leads to an increased probability of various types of failures [10,11]. Consistent effort has been invested to prevent the thermal runaway of onboard batteries. To understand the battery faults mechanisms, Wu et al. reviewed the recent research on battery aging mechanisms. Besides, the state estimation accuracy influences the performance of the battery management system (BMS) [12]. Shrivastava et al. executed a review and analysis of the existing advanced state estimation methods [13]. They also proposed the comprehensive co-estimation method for battery states, which could effectively make use of the existing correlation between different battery states and reduce computational expense [14]. Gu et al. aimed to design an easy-to-implement diagnosis method that does not require accurate mathematical modeling, expert understanding, and complex computational process [15]. It is necessary to implement an effective and reliable fault diagnosis method of the battery system based on the recognition of the battery system fault initiation mechanism. Early warning of battery faults is required to improve the safety and reliability of the real application of the battery system [16].

As for battery system fault diagnosis, researchers have conducted a lot of exploration in terms of fault triggering mechanism, behavior characteristics, and reaction mechanism [17–19]. A further understanding of battery system faults has been obtained, and a preliminary fault diagnosis strategy has been developed based on the external characteristic behavior exhibited by the occurrence of faults. In this paper, the fault diagnosis of battery systems in new energy vehicles is reviewed in detail. Firstly, the common failures of lithium-ion batteries are classified, and the triggering mechanism of battery cell failure is briefly analyzed. Next, the existing fault diagnosis methods are described and classified in detail. Finally, the perspective of future development in battery fault diagnosis technology is summarized.

2. Battery Fault Mechanism

During the practical use of new energy vehicles, battery performances are influenced by a variety of factors. In this section, different types of battery faults in new energy vehicles are introduced and the failure mechanisms of the battery system are elaborated in detail.

2.1. Battery Fault Types

Common lithium-ion battery systems mainly include cells, BMS, sensors, connection components, etc. Due to the complex internal operation mechanism and external user conditions, there are various types of faults in lithium-ion battery systems and complex fault evolution patterns. From the perspective of the control system, battery system fault modes can be divided into two main types, including cell fault and system fault, respectively. Cell fault is the dominant factor affecting the safety of battery systems, which can be further divided into progressive faults and sudden faults. System faults can be classified as management system faults, sensor faults, and connection component faults. This subsection will elaborate on the different types of battery faults, as shown in Figure 1.

2.1.1. Cell Fault

Lithium-ion batteries can fail during actual operation due to changes in their internal structure or characteristics. According to the different development stages of cell fault, it can be mainly divided into two types: progressive fault and sudden fault.

Progressive fault is mainly caused by battery degradation, which is essentially a superposition of a series of internal battery side reactions and is affected by both internal and external battery environments. During the charge and discharge cycle, abnormalities such as loss of active material, electrolyte consumption, increase in internal resistance, lithium deposition, gas generation, SEI thickening, and current collector corrosion will occur inside the battery [20–22]. External stimulation and internal side reactions lead to continuous loss of cell active components and accumulation of insoluble by-products [23]. The consequent shift in electrochemical equilibrium can cause the battery degradation highly nonlinear and leads to high overpotential, low-rate capability, and especially limited lifespan, which hinders the battery's commercial application. Therefore, timely detection of progressive faults and accurate assessment of battery health conditions can provide a strong guarantee for safe battery operation.

Sudden fault is a failure that causes sudden failure or significant degradation of the battery system without obvious signs or within a short period, including internal short circuits [24], thermal runaway, capacity diving, liquid leakage, etc. Sudden fault and progressive fault are equivalent to two successive processes in the reaction time sequence, and the final stage of progressive fault development is to trigger a sudden fault. For example, unreasonable charging and discharging strategies can lead to internal lithium plating, causing battery capacity to fade, which is still a progressive failure. With the further evolution of lithium deposition, lithium dendrites can penetrate the separator, triggering internal short circuits [25]. Massive heat is released and even triggers thermal runaway in a short period [26], which is a sudden failure. Therefore, progressive faults can develop into sudden faults through continuous evolution. However, the occurrence of sudden faults does not depend entirely on the evolution of progressive faults. In addition to battery degradation, other battery external factors can also directly lead to the sudden faults of batteries. For example, the battery in the use process, due to mechanical abuse resulting in an internal short circuit, can generate a lot of heat in a short period, which can lead to thermal runaway, smoke, fire, or even explosion [27].

2.1.2. System Fault

Battery system fault consists of the following three main types, management system fault, sensor fault, and connection component fault, respectively.

Management system fault: In the field of new energy vehicles, the function of power BMS mainly contains two aspects, which are monitoring and management. That is a real-time estimation of battery performance parameters and effective control of battery temperature according to the application environment [28]. BMS is the core control unit, its normal performance is significantly important to ensure the safe, stable, and reliable working condition of the battery [29]. The battery management system enables the safe monitoring of power cell characteristics by collecting external characteristics of the power cell system [30,31]. If the BMS fails, it will send an error command and interfere with the proper operation. The functions will be limited, and in severe cases, irreversible damage will be caused to the battery, which will lead to a series of chain failures [32]. For example, the failure of the equalization component of the BMS can lead to increased inconsistency in the battery system and affect the system's performance. If the charging and discharging control components of the BMS fail, it will cause an increased risk of overcharge and overdischarge and reduce the battery life. If the temperature control component of the BMS fails, it will cause the battery system to operate at an abnormal temperature, which may lead to thermal abuse and even cause thermal runaway [33]. The development of BMS with a high level of functional safety is a hot issue for the industry, which needs to be solved from different aspects such as the design process, software, and hardware.

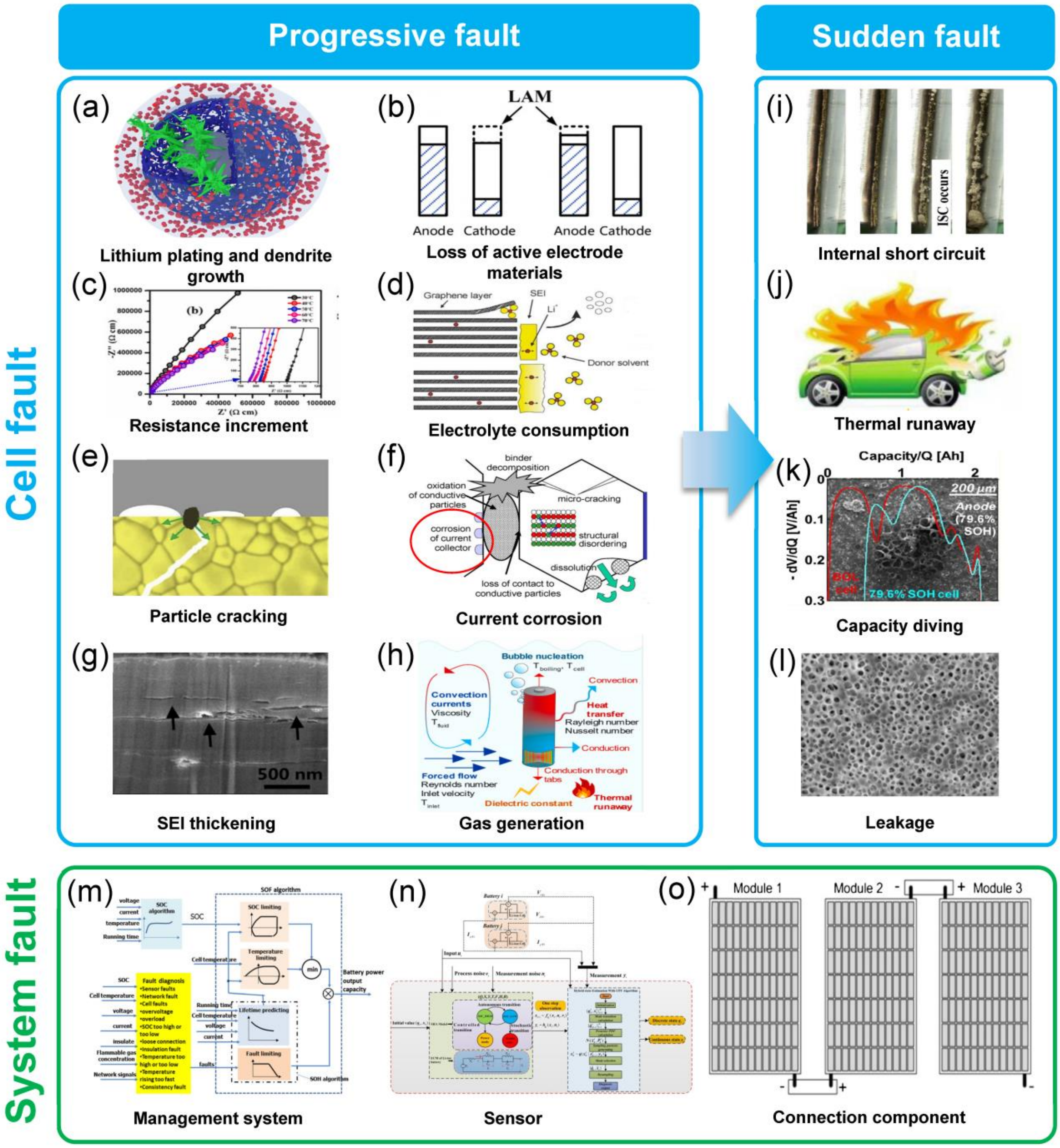

Figure 1. Battery fault can be divided into cell fault (**a**–**l**) and (**m**–**o**) system fault. (**a**) Three-dimension schematic for Li deposition [34]. Reproduced with permission from Elsevier. (**b**) The consumption of active electrode materials. (**c**) Impedance profiles of the batteries [35]. Reproduced with permission from Elsevier. (**d**) Electrolyte consumption at the anode/electrolyte interface [36]. Reproduced with permission from Elsevier. (**e**) Mechanical failure of ceramic electrolyte [37]. Reproduced with permission from Elsevier. (**f**) Current corrosion of cathode materials [36]. Reproduced with permission from Elsevier. (**g**) Cross-sectional image of thickening SEI [38]. Reproduced with permission from Elsevier. (**h**) Modeling of gas generation [39]. Reproduced with permission from the Elsevier. (**i**) Lithium dendrite-induced internal short circuits in lithium-ion batteries [40]. (**j**) Thermal runaway accident [41]. (**k**) Cell capacity loss [42]. (**l**) SEM images of the prepared porous membranes [43]. (**m**) Battery state estimation algorithm framework [44]. (**n**) Fault diagnosis scheme of sensor [45]. (**o**) Battery component connection fault [46].

Sensor fault: The sensor measurements can be used to update the model parameters in the battery management system in real-time to achieve highly accurate monitoring and management of the battery. The battery management system is dependent on the suitable operation of temperature, voltage, current and other sensors to achieve battery state estimation, charging and discharging control, fault diagnosis, equalization control, temperature control, and other functions. There are three main types of battery sensor faults, including voltage sensor fault, current sensor fault, and temperature sensor fault, respectively [45]. During usage, there will be inevitable faults such as deviation, drift, decrease in accuracy level, or even stopping working. Once the sensor fault is not detected in time, it can lead to the current, voltage, temperature, and other data cannot be measured or can be measured inaccurately, affecting the accuracy of multi-state estimation of battery SOC, SOH, SOT, etc. It is difficult to make accurate and reasonable judgments on the current working state of the battery, inducing the BMS system to stop working or posting wrong commands. However, lithium-ion batteries must operate within safe voltage and temperature ranges, and exceeding these ranges can lead to reduced battery performance, equalization errors, and even thermal runaway accidents. Generally, compared with sensor-stopping faults, sensor faults such as deviation, drift, and accuracy level reduction are more hidden and more difficult to diagnose, which is the focus and challenge of the current sensor fault diagnosis technology research [47].

Connection component fault: The battery connection component fault tends to be induced by a bad connection between battery terminals. Connections between individual cells in a battery pack or between battery modules need to be made by nuts or welding processes. With the increase in vehicle running time and the uncertainty of operating conditions, the vibration, corrosion of components, and expansion of battery gas production can trigger the failure of internal connection components of the battery system, such as loose nuts or welding joints and poor contact [46,48]. If a false connection occurs between cells, it can affect the power performances of the battery system at high rates, resulting in insufficient battery output power. If such faults are not effectively detected and eliminated for a long time, they can cause the resistance to increase rapidly. Excessive internal resistance can lead to a continuous accumulation of local heat, which can result in an increase in the temperature of the battery and connections, causing accelerated degradation of the battery or even thermal runaway safety accidents [49].

2.2. Battery Fault Mechanism

The study of the fault mechanism of battery can help us understand the occurrence and evolution of the fault pattern, so as to provide a scientific basis for the development of fault diagnosis methods. This subsection briefly introduces the causes and mechanisms of different faults. Currently, there are mainly overcharge, overdischarge, overcool, overheat, large rate charge and discharge, inconsistency, and other factors that may lead to battery failure, as shown in Figure 2.

Overcharge: In order to meet the voltage and capacity requirements of automotive power sources, the battery system consists of many individual cells connected in series or parallel. However, there are inconsistencies between individual cells due to manufacturing defects and differences in operating conditions [50]. During charging, overcharging of some individual batteries will inevitably occur due to problems such as battery charger failure or inaccurate detection or estimation of battery state (e.g., SOC) in the battery management system [51]. Even if the total voltage of the battery system remains relatively below its limit, some individual cells can still be overcharged [52]. Generally, when a battery is overcharged, lithium plating will occur on the surface of the anode. If there is a slight overcharge for a long period, it will lead to a progressive fault in the battery capacity fading too fast due to the loss of active lithium. At the same time, lithium plating may induce lithium dendrites, increasing the safety risk of micro or internal short circuits caused by separator penetration. In some extreme cases, such as when a BMS failure occurs, a long period of deep overcharge of the battery can occur. The battery temperature continues to rise, triggering a series of side reactions such as SEI film decomposition and cathode material decomposition [53], which eventually trigger sudden failures such as internal short circuits and thermal runaway of the battery [54,55].

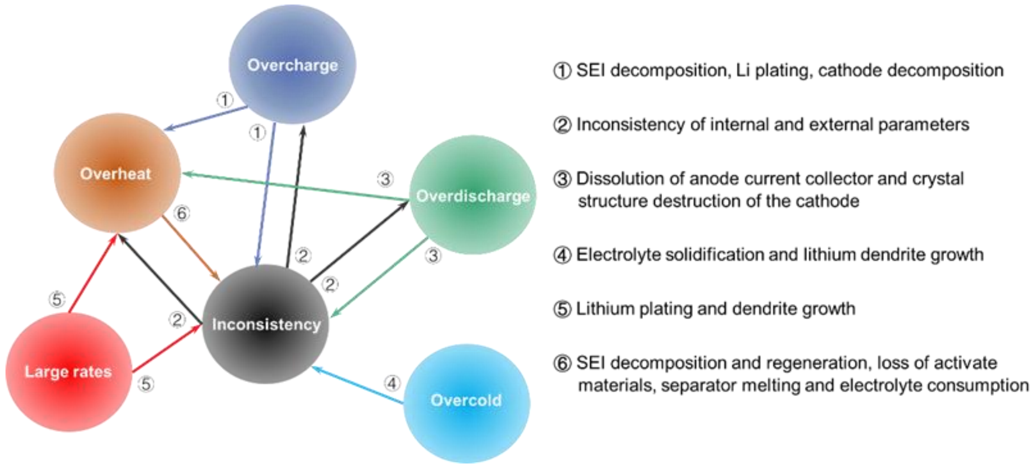

Figure 2. Battery fault mechanisms and the internal coupling relationships. The six main battery failure mechanisms are coupled with each other and are not singularly induced.

Overdischarge: Generally, the overdischarge is prevented by setting the discharge cut-off voltage. However, overdischarge is still a common trouble in electric vehicle applications due to high current inrush, unreasonable design of battery management system, long battery storage time, and unbalance between battery modules. As for the long-term slight overdischarge situation, the anode structure and the SEI film are easily damaged due to the complete deintercalation of lithium ions. It leads to irreversible loss of active material and triggers a progressive fault in which the battery capacity fades quickly. If a long period of deep overdischarge occurs, the lithium-ion stripping ability of the anode decreases. Battery polarization voltage rises, causing the negative current collector copper foil to be oxidized, dissolved, and deposited on the cathode surface. On the one hand, it affects the electron transport capacity of the negative current collector and hinders the deintercalation of lithium ions, resulting in the progressive fault of rapid fade of battery capacity and rapid increase of internal impedance [56]. On the other hand, copper deposited on the surface of the cathode may penetrate the separator, triggering sudden faults such as internal short circuits and thermal runaway of the battery [17]. In addition, deep overdischarge can cause excessive lithium embedding in the cathode, triggering irreversible damage to the crystal structure of the cathode material and leading to degradation of the battery performance [57].

Large rate charge and discharge: As the charge and discharge rate of the battery increases, the heat production rate increases consequently. It is easy to trigger exothermic side reactions inside the battery, increasing the risk of internal short circuits, and can cause sudden fault of the battery thermal runaway [58,59]. Especially for the large rate charging process, due to the solid phase diffusion rate limitation, the lithium plating tends to occur at the anode surface. It causes progressive fault of capacity fading, and induces lithium dendrite growth, causing internal short circuits as a safety hazard.

Overheat: Battery charging and discharging process will be accompanied by the violent movement of electrons, the result of this violent movement is the thermal effect. Many conditions can cause abnormal battery heating, such as side reactions during overcharge and overdischarge, external short circuits, internal short circuits, insufficient cooling system heat dissipation capability, etc. When the battery is at a relatively high operating temperature, it can increase the rate of internal side reactions, such as the rate of SEI decomposition and regeneration. It leads to an accelerated rate of irreversible loss of active material and triggers a progressive fault in which the battery capacity fades quickly [60,61]. In the charging and discharging process, if the battery working environment temperature is too high and the heat production rate is significantly higher than the heat dissipation rate, the lithium-ion battery may have different degrees of expansion. It can cause resistance increase and cycle life degradation, which triggers a series of exothermic side reactions such as electrolyte consumption and separator melting. The degradation of cathode material and the growth of solid electrolyte interfacial in the anode can be accelerated, which eventually leads to sudden faults such as internal short circuits and thermal runaway of the battery. If the decomposition of the materials inside the lithium-ion battery produces gas, the increased pressure will cause the battery to expand and possibly explode.

Overcool: When the battery is in a low-temperature operating environment, it may cause some of the solvents in the electrolyte to condense and solidify. Lithium-ion diffusion or migration rate becomes significantly smaller. Especially for the low-temperature charging case, there is a mismatch between the electrochemical reaction and the solid phase diffusion rate. The ionic conductivity of the SEI and electrolyte and the diffusion of lithium into the graphite can be decreased significantly, resulting in the battery capacity fading rapidly [62,63]. The lithium plating on the surface of the anode tends to occur, and the uncontrollable dendrites can cause a series of sudden faults such as separator penetration, internal short circuit, etc., [64,65].

Inconsistency: In the various stages of battery manufacturing, screening into groups and usage, there is a certain degree of inconsistency in internal and external parameters such as available capacity, internal resistance, open-circuit voltage, self-discharge rate, and charge state among the individual cells in the battery system, which can affect the system efficiency, safety, and service life [66,67]. Generally, with the charging and discharging cycles, the inconsistency among the individual cells tends to gradually increase due to the different degradation histories, which affects the overall capacity of the system. For example, in the screening stage, the low available capacity cell can be fully charged and discharged during actual operation, or even overcharged and overdischarged. It will accelerate the degradation process, which will eventually lead to premature battery failure, and the whole battery system will also show the progressive fault of capacity fade. Therefore, it is an important part of battery fault diagnosis to identify and locate the faulty single unit in advance and implement targeted operation and maintenance through real-time and accurate assessment of battery system inconsistency.

The trigger mechanism of battery cell fault is complex and requires optimal design and regulation at all stages of battery manufacturing, screening into groups, and use to improve battery system safety. During the actual operation, the electric and thermal management strategies are optimally designed to avoid abnormal operations such as overcharge, overdischarge, overcooling, overheating, and large rate charging and discharging as much as possible. It can delay the rate of capacity fade and internal resistance increase, reducing the risk of lithium plating, micro or internal short circuit, thermal runaway, etc. By designing a reasonable battery cell fault diagnosis technology to achieve accurate early identification of faulty cells, it can provide support for targeted operation and maintenance of the safety and reliability of the battery system.

3. Fault Diagnosis Method

The battery system itself is a complex, strongly nonlinear, and time-lagged system. Based on the information on current, voltage, temperature, etc., [68]. collected in real-time, a reasonable fault diagnosis system can be designed to realize fault warnings. It can feedback on fault information to the battery management system to take necessary protection measures to guarantee the safe, stable, and reliable working condition of the battery system. Currently, the methods used for battery system fault diagnosis mainly include model-based, data-driven, knowledge-based, and statistical analysis-based methods, as shown in Figure 3. Furthermore, Table 1 shows the fault diagnosis methods and typical fault diagnosis cases.

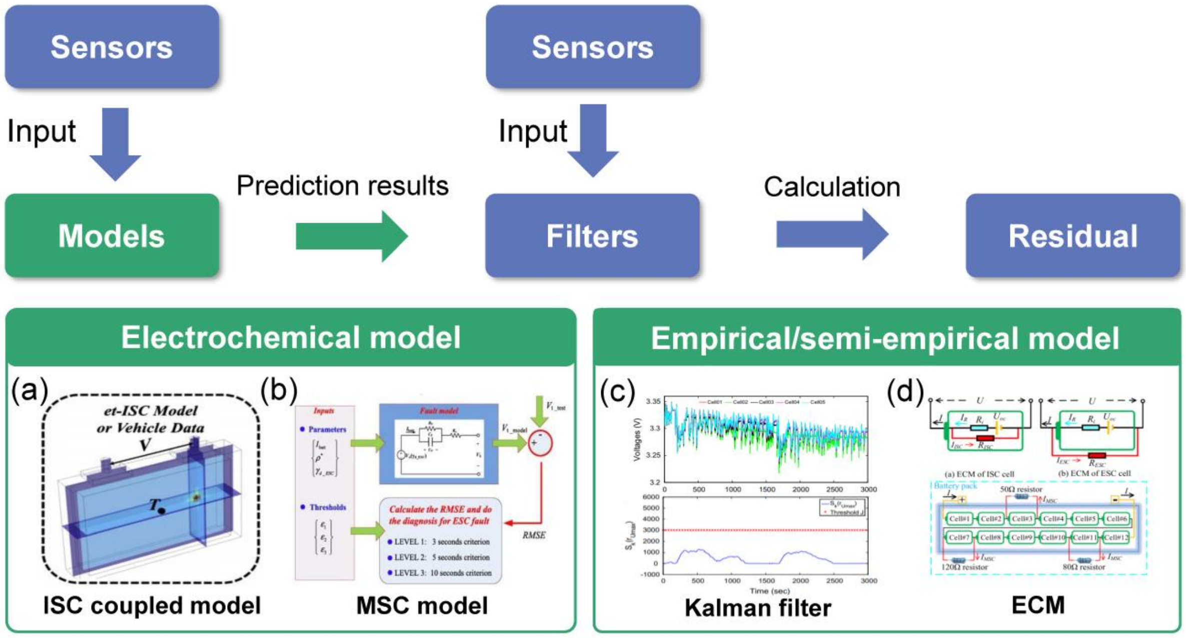

Figure 3. The fault diagnosis models mainly include (**a**,**b**) the electrochemical model [69,70] and (**c**,**d**) the empirical/semi-empirical model [71,72]. The model-based battery fault diagnosis algorithm is to establish a lithium-ion battery correlation model, generates residuals by comparing the predicted values of the model with the real values measured by sensors, and then evaluates the residuals to achieve fault diagnosis.

3.1. Model-Based Methods

The model-based fault diagnosis method requires that the estimated values derived from the battery-related model are compared with the actual measured values, and the difference between the two produces the system residuals. The residual can be used as a fault signal, and this signal can be used to further analyze the fault characteristics and provide theoretical data support for system fault diagnosis. Noted that system residuals should, ideally, contain only fault information. With the help of battery models and measurement data, many researchers have used observers or filters to perform state or parameter estimation and use the difference between the estimated and actual values to determine faults. Generally, battery models can be divided into two types, that is, the electrochemical models and empirical/semi-empirical models.

The electrochemical model of a lithium-ion battery can further connect the internal microscopic mechanism of the battery with engineering applications by solving the complex coupling relationship between multiple physical fields such as electric field, concentration field, thermal field, and electrochemical reaction, thus playing an active role in the design of battery structure and battery thermal management system. Feng et al. proposed a method for online detection of internal short circuit faults based on a three-dimensional electrochemical-thermal-internal short circuit coupling model, which uses the least squares method based on the forgetting factor for online parameter estimation to achieve internal short circuit detection [70]. However, the method was not experimented and was not validated in practical applications. After that, they proposed a model-based fault-diagnosis algorithm for online internal-short-circuit detection [73]. This algorithm can transform the measured voltage and temperature to the intrinsic electrochemical status that can reflect typical internal-short-circuit features, relying on the theory of model-based control. Furthermore, they constructed a coupled electrochemical-thermal model to predict the voltage drop and temperature increase during thermal runaway [74]. The coupled model could capture the underlying mechanism, including capacity degradation under high temperatures, the internal short circuit caused by the thermal failure of the separator, and the chemical reactions of the cell components that can release heat under extreme temperatures. Kong et al. constructed a pseudo-two-dimensional model of micro internal short circuit batteries, revealing the phenomenon of electric quantity depletion and the variation of internal electrochemical parameters. The effective electric conductivity of the separator found a crucial parameter that could describe the internal short circuit severity. They determined reasonable values for this effective conductivity for fault diagnosis and battery design [75]. Seo et al. estimated the short-circuit resistance by optimizing the short-circuit model within a lithium-ion battery through a switching model. The Open Circuit Voltage (OCV) and state of charge (SOC) were estimated by the recursive least squares method by combining the OCV and SOC curves, and the short-circuit resistance was estimated based on the variation of the estimated OCV and SOC [76]. Gao et al. aimed to quantitatively analyze micro-short-circuit in an initial stage. An equivalent micro-short-circuit experiment was carried out to verify the feasibility of the proposed method [77]. Zhao et al. proposed a modified electrochemical-thermal model, which can incorporate an additional heat source from the nail site and prove to be successful in depicting temperature changes in batteries. This model was able to estimate the occurrence and approximate start time of thermal runaways [78]. Presently, the electrochemical model is developing toward multi-dimensionality, multi-scale, and multiple electrode materials, further establishing accurate mathematical models and laying the foundation for optimal design of power batteries.

The empirical/semi-empirical model uses battery measurement data to generate residuals to detect faults through state and parameter estimation techniques. Due to its simplicity and convenience, it is widely used for fault diagnosis of battery components and battery packs. He et al. utilized the adaptive extended Kalman filter to estimate the states of each individual battery. The estimated values are compared with the measured values to determine the fault [72]. Besides, Liu et al. presented an effective model-based sensor fault detection method with low computational effort. The estimated output voltage from the adaptive extended Kalman filter is compared with the measured voltage to generate a residual. The residuals can be evaluated to determine the occurrence of fault [79]. Ouyang et al. developed an internal short circuit detection method based on battery consistency within the battery pack. This method employs the recursive least square algorithm, which derives from the equivalent circuit model [80]. Alavi et al. obtained an estimation of the Li^+ transport rate in electrodes and compared it with the boundary values in order to generate an appropriate fault alarm of lithium plating [81]. Dey et al. proposed a partial differential equation model to detect thermal faults in lithium-ion batteries. The distributed parameter 1-D thermal model for the cylindrical battery was utilized combined with partial differential equation observer-based techniques [82].

3.2. Data-Driven Methods

With the rise of artificial intelligence, data-driven fault diagnosis methods have gradually become a research hotspot. The data-driven fault diagnosis method does not require a precise analytical mathematical model of the system, and the fault detection and separation of the system is completed mainly by analyzing and processing the system process operation data with the help of relevant technical means. The battery fault is diagnosed by learning the potential fault occurrence pattern from a large number of battery training samples.

The data-driven methods require to construct the relationship between fault features and fault labels. However, the fault data tends to take a lot of time to obtain, making the methods difficult to apply in real applications. With the rapid development of cloud computing platforms, there is a dynamic increase in the speed of data collection, resulting in a great breakthrough in data size and quality. Combined with the powerful computing ability, data-driven methods have gradually been employed to achieve online battery fault diagnosis [83]. Machine learning algorithms can be classified into four types based on problem attributes, that is, regression, classification, clustering, and dimensionality reduction, as shown in Figure 4. The data is first collected and pre-processed and then used to train and optimize the data-driven model. The optimized model is used to predict and analyze the actual data and to achieve fault diagnosis. Chen et al. proposed an online two-step prediction approach for the maximum temperature rise. The experimental data were used to validate the approach, and the mean absolute error of prediction results was 3.05% [84]. Kim et al. proposed a data mining-based real-time fault diagnosis for multicell lithium-ion batteries using a microcontroller. The physical model parameters and operation states were estimated and utilized to detect abnormal batteries, identifying the types of faults such as internal short circuits and anomy-aged cells [85]. Zhao et al. presented a fault diagnosis method for battery systems in electric vehicles based on the machine learning method [83]. The 3σ multi-level screening strategy was applied to detect and analyze the abnormal changes of cell terminal voltages in a battery pack in the form of probability [86]. To validate the diagnosis model, the actual vehicle operating data is utilized. Jiang et al. proposed a fault diagnosis method with an isolated forst algorithm. The original voltage data can be decomposed into static components, reflecting anomalous information [87]. Yang et al. proposed a random forests-based classification method to identify the electrolyte leakage behavior during external short circuit fault experiments. Furthermore, a three-step model-based diagnosis algorithm for identifying the external short circuit fault was proposed [88]. Xia et al. proposed a fault diagnosis method for battery fault diagnosis based on supervised statistical learning. The statistical properties of fault were captured based on the maximum likelihood estimator and the excellent performance of the proposed method in dynamic conditions was demonstrated with the validation experiments [89]. Hong et al. utilized long short-term memory recurrent neural network to develop a novel deep-learning enabled method, performing accurate voltage prediction for battery systems. The battery safety can be assessed by predicting battery voltage to diagnose the occurrence of faults and decrease runaway risk [90].

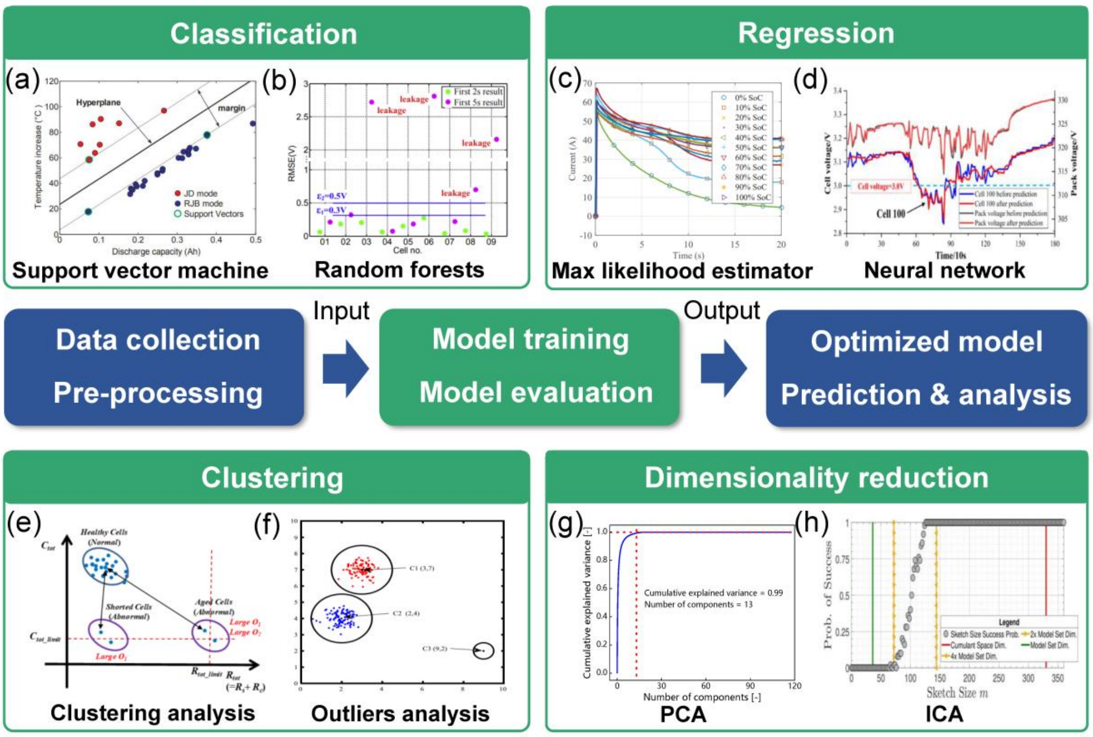

Figure 4. The data-driven methods can be divided into (**a**,**b**) classification [84,88], (**c**,**d**) regression [89,90], (**e**,**f**) clustering [83,85], and (**g**,**h**) dimensionality reduction [91,92]. Data-driven battery fault diagnosis algorithm directly analyzes and processes a large amount of offline and online operational data of batteries, establishes a mapping mechanism between the input and output of batteries, and extracts the corresponding features for fault diagnosis.

3.3. Statistical Analysis-Based Methods

The fault diagnosis method based on statistical analysis is analyzed using statistical methods such as information entropy, normal distribution, correlation coefficient analysis and other methods directly based on the current, voltage, and temperature data obtained from the signal acquisition system, setting reasonable abnormality coefficients and thresholds [93], as shown in Figure 5. Xia et al. proposed a fault detection method for battery faults of short circuits based on the correlation coefficient. This method can utilize the direct voltage of the battery cell and does not require any additional hardware [94]. Wang et al. utilized the modified Shannon entropy to propose an in-situ voltage fault diagnosis method, which can predict the voltage fault in time by monitoring battery voltage during operations [95]. Ma et al. proposed a connecting fault detection method of lithium-ion batteries in series. The cross-voltage test was adopted to recognize the increase in contact resistance and internal resistance [96]. Cao et al. proposed an internal short circuit diagnosis algorithm for battery packs through voltage anomaly detection. The mean-difference algorithm was applied to characterize large battery packs. The diagnosis of an internal short circuit was approached based on residual analysis [97]. Liu et al. utilized sequential residual generation with structural analysis theory. The structural analysis can deal with the pre-analysis of sensor faults without the demands of the accurate detection of battery parameters, which is efficient during the early design stages of fault diagnosis [98]. Fan et al. constructed a generalized dimensionless indicator with a tolerance factor and mapped it to 2-dimensional space to represent voltage evolution patterns. Then the local outlier factor algorithm was used to find the anomalies pattern and identify faulty batteries [99]. These methods have low computational complexity and high execution efficiency. It can extract useful fault characteristics directly from the battery measurement data to achieve faults diagnosis, without the necessity of building accurate battery analysis models, and is proper for a wide range of applications. However, it tends to be possible to achieve fault detection, and it is difficult to identify the type of fault.

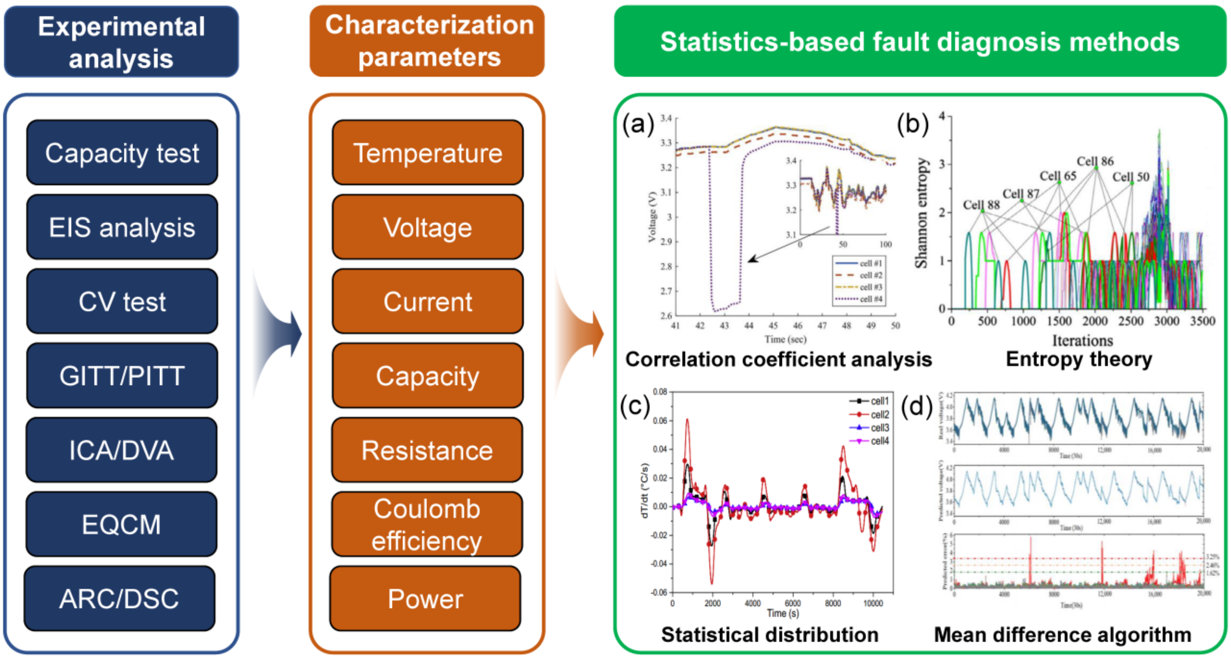

Figure 5. The statistical analysis-based methods include (**a**) correlation coefficient analysis [94], (**b**) entropy theory [95], (**c**) statistical distribution [96], (**d**) mean difference algorithm [97], etc. The statistical analysis method is based on a large number of experimental analysis techniques to obtain the characteristic parameters of the battery and uses statistical methods to analyze the collected data to achieve battery fault diagnosis.

3.4. Knowledge-Based Methods

Knowledge-based power battery fault diagnosis method research started early and is widely applied. This type of method does not require the use of complex mathematical models and relies on the understanding of battery mechanisms and the knowledge and experience accumulated over time to make fault judgments through intellectualization in concepts and processing methods, which can establish the connection between specific faults and fault data characteristics [100]. The main knowledge-based fault diagnosis methods are expert systems, fault trees, threshold rules, etc.

The expert system method is the most studied and widely used class of fault diagnosis techniques [101]. The key to this method is the size of the system knowledge base and the design of the reasoning machine, and a comprehensive and effective knowledge database can greatly help the reasoning judgment results. Huber et al. [102] utilized the expert knowledge to derive a database and proposed a method consisting of five phases. Chao et al. utilized fuzzy logic algorithms to determine different battery failure situations, extracting electric parameters and incremental capacity parameters under dynamic conditions as features [103]. Anwar et al. used a fuzzy logic-based residual evaluation algorithm to detect battery faults, constructing an electrochemical model to generate residual signals for voltage, temperature, and state of charge [104]. The expert system method does not require mathematical models and is easy to understand [11]. However, there are still limitations such as difficulty in acquiring knowledge and poor self-adaptation and learning ability. The fault tree analysis method is a practical method for the safety and reliability analysis of power battery systems [44]. The fault diagnosis network can be constructed based on various components in the system [105]. Singer utilized the fault tree and reliability analysis method to give a picture concerning tolerances of the probability values of hazards. The construction of a correct and reasonable fault tree is the core and key of diagnosis, once the fault tree is incomplete or incorrect, this diagnosis method will be useless [106]. Fault diagnosis based on threshold rules is now widely adopted by vehicle remote supervision platforms due to its easy setting of thresholds and low method difficulty factor. The threshold is established by utilizing a historical database and the rich experience of domain experts. Zhu et al. proposed a safety management method to mitigate the impact of overcharge and avoid the thermal runaway risk. The sharp drop in voltage before thermal runaway was used to provide a feasible approach to forewarn the impending risk [107]. Xiong et al. proposed a threshold rule-based detection method for overdischarged lithium-ion batteries. According to the temperature increase and voltage decrease during battery overdischarge, respectively temperature and voltage rules were established, and the Boolean expressions were used to directly give fault detection and early warning through Boolean expressions. However, in practical applications, the appropriate rules or time [108]. Liu et al. used each time step length of all cell voltage values as an indicator and used the entropy value method to obtain the target weights of each indicator. Based on the combined score and threshold value, the cells can be accurately identified voltage anomaly [109].

Table 1. Summary of fault diagnosis methods and typical fault diagnosis cases.

Methods	Techniques	Fault Types	Algorithm Properties	Typical Examples
Model-based methods	Kalman filter	Overcharge, overdischarge, sensor faults	Insensitive to noise; high computational complexity	Present an effective sensor fault detection and isolation scheme based on extended Kalman filter [72]
	Particle filter	Lithium plating	Insensitive to noise; large computational effort	Combine the particle filter and electrochemical models to diagnosis lithium plating [81]
	Partial differential equations	Thermal faults	High accuracy; complex	Approach real-time diagnosis for thermal faults based on PDE model [82]
	least squares method	Internal short circuit, micro short circuit	Low computational cost and high accuracy; low fault tolerance	Approach real-time ISC detection based on the combination of least squares method and coupled electrochemical model [70]
	Luenberger learning observers	Fault caused by internal resistance, thermal faults	It can assess faults quantitatively; it's noise sensitive and less robust	Detect and isolate three main thermal resistance faults based on Luenberger learning observers [110]
	Non-linear observer	Thermal faults	High accuracy, simple; the parameters identification is difficult	Approach battery thermal faults detection based on non-linear observer [111]
	Equivalent circuit model	Faults related with voltage and current	Simple and convenient; poor universality	Approach the identification of battery micro-short circuit based on equivalent circuit model [71]
Data-driven methods	Support vector machines	External short circuit	Excellent robustness; heavy computing	Approach a two-step prediction of max temperature rise based on SVM [84]
	Neural networks	Short circuit, performances	High accuracy; it depends on amount and quality of data	Approach accurate multi-forward-step voltage prediction based on LSTM [90]
	Clustering analysis	Short circuit	Simple and fast; it's sensitive to outliers and noise	Approach fault diagnosis for multi-cell batteries based on clustering analysis [85]
	Random forest	Leakage	No feature selection; it requires large amounts of training data	Approach the identification of leakage based on random forests algorithm [88]
Knowledge-based methods	Expert system methods	Both internal and external battery faults	No mathematical models required, convenient; the knowledge base is difficult to access	The expert knowledge is used to derive a database [102]
	Fuzzy logic	Sensor fault, connection component fault	Highly fault tolerant and easy to implement; poor learning ability	The Fuzzy logic is used to control the observation noise [112]
	Fault trees	Sensor fault, overcharge and overdischarge	Clear cause-effect relationship; complex	Provide a picture concerning the tolerances of the probability values of hazards [106]
	Threshold rules	Overcharge, internal short circuit, connection component fault	Simple and fast; high false alarm rate	Mitigate the impact of overcharge and avoid the risk of thermal runaway [107]
Statistics-based methods	Entropy theory	Voltage fault, temperature fault, connection component fault	High diagnostic accuracy; sensitive to noise	Approach in-situ voltage fault diagnosis based on modified Shannon entropy [95]
	Statistical distribution	Connection component fault	Simple and convenient; sensitive to noise	The cross-voltage test is adopted to distinguish resistance fault [96]
	Mean-difference algorithm	Internal short circuit	Simple calculation; it needs to be integrated with other methods	The mean-difference model is applied to characterize large battery packs [97]
	Correlation coefficient analysis	Short circuit, voltage fault, connection component fault	Fast calculation speed; sensitive to measurement noise	Approach the fault detection for short circuits based on correlation coefficient of voltage curves [94]

4. Summary and Perspective

In this paper, a detailed review of battery fault diagnosis research is provided. Firstly, the types of battery faults are introduced, including cell faults and system faults. Then a comprehensive analysis of battery failure mechanisms is presented, including overcharge, overdischarge, overheat, overcool, large rate charge and discharge and inconsistency, etc. Researchers have carried out a large number of experiments and model simulations to reveal the battery fault mechanism, and further develop a series of diagnosis methods. Four major diagnostic methods are summarized for battery systems, including model-based, data-driven, knowledge-based, and statistical analysis-based methods, yet researchers continue to pursue more efficient and accurate battery fault diagnosis methods to ensure the safety of electric vehicles.

The traditional battery management system relies on the vehicle-side computing platform, which is limited by the storage capacity of embedded devices and can only achieve basic battery management functions such as data monitoring, equalization, communication, charge, and discharge control, etc. It cannot be adapted to advanced models and algorithms such as micro-macro coupled fine regulation of batteries and fault warning. The process of intelligence and networking provides an opportunity to solve this problem and promotes the development and application of a new generation of cloud-based battery management systems. This paper presents some new understandings for future battery fault diagnosis development, which can be summarized as follows.

1. Big data technology shows a good application prospect in the field of new energy vehicles. How to establish vehicle-level failure risk prediction and early warning based on electric vehicle operation data from the prospective of big data will become a hot spot for future research. Based on big data technology, the rapidly developing cloud management platform can provide the excellent organizational and computational ability for urgent demands of online battery fault diagnosis.
2. The rapid development of highly accurate sensors and 5G communication networks are important to obtain and transfer detailed battery data. The future high-precision battery fault diagnosis poses higher demands on the scale and quality of battery data. To achieve online fault diagnosis, the highly accurate sensors and 5G communication network can provide excellent data transfer ability, enabling the efficient fusion of large-scale data.
3. Multi-model fusion methods have the potential to achieve accurate battery fault diagnosis. The model-based methods have poor generalization ability. The data-driven methods have poor interpretability. The knowledge-based and statistical analysis-based methods have limited accuracy. Therefore, a single fault diagnosis method cannot meet the demands of battery fault diagnosis, which is strongly time-varying and has a non-linear complex vehicle environment. The joint estimation approach using multi-model fusion is expected to break the bottleneck limitation of a single model.
4. Vehicle-cloud collaboration platform can provide model and platform support for battery fault diagnosis. Traditional in-vehicle embedded systems have limited storage and calculation ability, and it is difficult to implement online accurate battery fault diagnosis. A vehicle-cloud collaboration battery fault diagnosis platform can be constructed based on the fusion of multi-dimensional fault diagnosis models. The rapid development of big data, 5G communication, and highly accurate sensors can break the network barrier between vehicle and cloud, achieving a high-performance information processing system to minimize the interaction expenses between system functions. The construction of a fault diagnosis-oriented vehicle-cloud collaboration management system can be expected to realize fine-grained online battery fault diagnosis.

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