Progress on the Fault Diagnosis Approach for Lithium-ion Battery Systems: Advances, Challenges, and Prospects

Hanxiao Liu, Luan Zhang, and Liwei Li

Abstract—**Because of their advantages of high energy and power density, low self-discharge rate, and long lifespan, lithium-ion batteries (LIBs) have been widely used in many applications such as electric vehicles, energy storage systems, smart grids, etc. However, lithium-ion battery systems (LIBSs) frequently malfunction because of complex working conditions, harsh operating environment, battery inconsistency, and inherent defects in battery cells. Thus, safety of LIBSs has become a prominent problem and has attracted wide attention. Therefore, efficient and accurate fault diagnosis for LIBs is very important. This paper provides a comprehensive review of the latest research progress in fault diagnosis for LIBs. First, the types of battery faults are comprehensively introduced and the characteristics of each fault are analyzed. Then, the fault diagnosis methods are systematically elaborated, including model-based, data processing-based, machine learning-based and knowledge-based methods. The latest research is discussed and existing issues and challenges are presented, while future developments are also prospected. The aim is to promote further researches into efficient and advanced fault diagnosis methods for more reliable and safer LIBs.**

Index Terms—**Battery management system, battery safety, fault diagnosis, lithium-ion battery system.**

I. INTRODUCTION

China has set a target of "carbon peaking by 2030 and carbon neutrality by 2060", and is vigorously developing applications of new energy sources [1], [2]. On the one hand, electric vehicles (EVs) are gradually replacing traditional fuel vehicles as the new mainstream means of transportation, and is the focus of development and competition around the world [3]–[6]. In addition, energy storage systems (ESSs) have been installed in large numbers to improve the power grid's capacity to absorb new energy generation [7]–[9].

A. Lithium-ion Battery Systems

Lithium-ion batteries (LIBs) have been widely used in EVs and ESSs because of their advantages of high energy/power density, low self-discharge rate, no memory effect, long lifespan, low level of pollution and light weight [10]–[14]. However, in recent years, fire and explosion accidents of EVs and ESSs caused by LIB faults have occurred frequently [15]. Consequently, the safety of lithium-ion battery systems (LIBSs) has attracted widespread attention, and the safety threat from LIBs has become a prominent problem [16].

B. Faults in LIBSs

There are some potential safety problems in LIBs, which may threaten the life and property of consumers [17]. Temperature has a significant impact on LIB performance. At high temperature, LIBs may experience self-discharge and capacity degradation. More seriously, an exceptionally hot environment might lead LIBs to overheat, and this could even trigger a thermal runaway (TR) and eventually result in fire and explosion [18]. On the other hand, low temperature conditions can lead to increased charge-transfer resistance at the electrode-electrolyte interface, thus causing EVs to lose a significant amount of power and have a reduced driving mileage [19]. Typically, the optimum operational temperature range of a battery is from 25℃ to 55℃. When the temperature exceeds 60℃, its heating starts to be taken over by thermal abuse reactions [20]–[22]. With the development of LIB technologies, the specific energy of an LIB increases dramatically and the separator gets thinner, which reduces the thermal stability of LIBSs [23]. At the same time, in order to meet the needs of voltage, current, power, and energy, a large amount of battery cells are connected into battery modules, battery packs, and even battery clusters via series-parallel connections [24], [25]. The extensive use

Received: October 12, 2023
Accepted: April 3, 2024
Published Online: September 1, 2024
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DOI: 10.23919/PCMP.2023.000213

of connection components raises the complexity of LIBSs and increases the probability of different faults and safety accidents [26]. In EVs, the operating conditions of LIBSs are complex and the working environment is harsh. For example, LIBSs of EVs suffer from frequent vibration, impact, and experience low temperature conditions, as well as generating a lot of heat inducing temperature rise during the normal operating process [27]. This may lead to safety hazards.

LIBS of EVs consists of LIB packs, sensors, battery thermal management systems (BTMSs), battery management systems (BMSs), connectors and so on [28]. A BMS is deployed to guarantee the safety and performance of LIBSs [29]. It performs state estimation, state monitoring, thermal management, fault diagnosis and prognosis, and fault-tolerant control for efficient and safe working [30]. The role of BTMSs is to maintain the temperature of battery within its safe range to ensure its reliable operation even in higher load conditions [31]–[33].

As shown in Fig. 1, according to the location of the fault, the common faults in LIBSs can be roughly divided into four categories: battery abuse faults which includes internal short circuit (ISC), external short circuit (ESC), overcharge and over-discharge faults [34], [35]; sensor faults; connection faults; and other faults such as BMS malfunction, contactor faults, etc. If faults can be detected at an early stage and fault-tolerant control is conducted, it is possible to prevent the worsening of the faults and mitigate potential harm to people and property [36], [37]. Consequently, performing efficient and accurate fault diagnostics for LIBSs is critical.

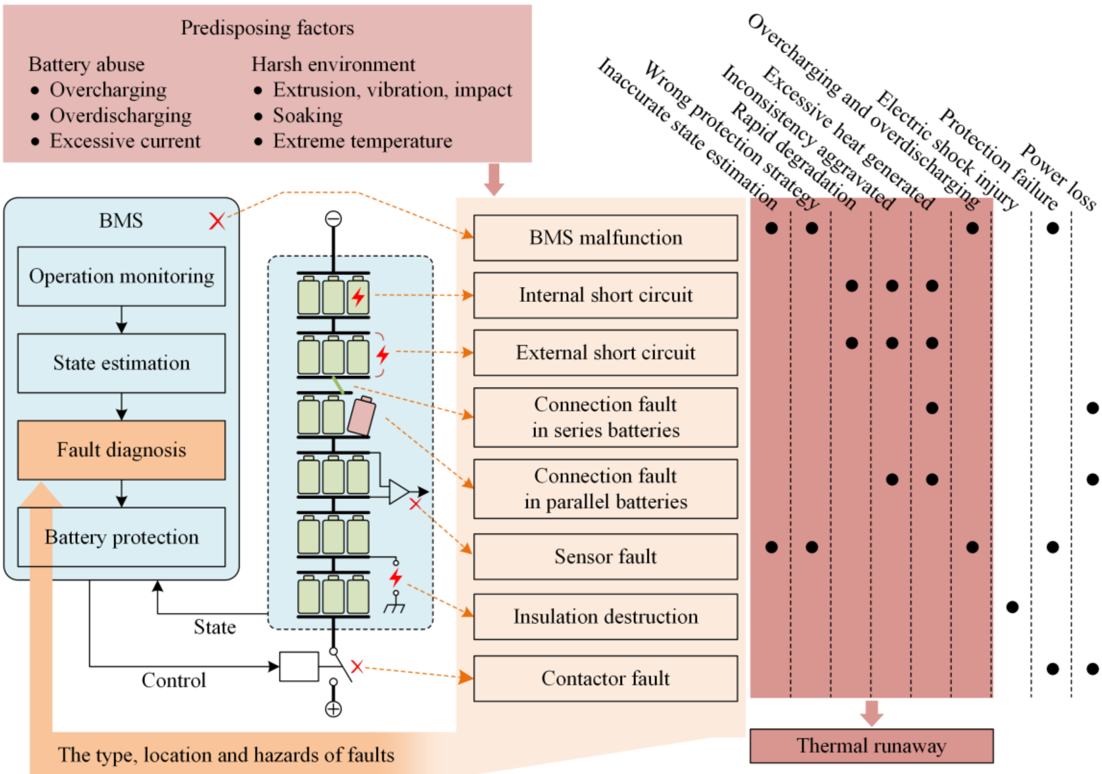

Fig. 1. The functions of BMS and the causes, types, and hazards of faults in LIBs.

C. Objective

The main objective of this work is to clearly demonstrate the fault types in LIBs, systematically summarize the current fault diagnosis methods, elaborate the current research progress on fault diagnostics, present the existing issues and challenges of fault diagnosis research, and prospect the future development trends of fault diagnosis for LIBSs.

The remainder of the paper is structured as follows. Section II introduces the fault types in LIBs and analyzes the mechanism and characteristics of each type of fault. Section III systematically summarizes the fault diagnosis methods and describes the characteristics of each type. Section IV focuses on the current research in fault diagnosis, while Section V discusses the existing issues and challenges and outlines the development trends of fault diagnosis. Section VI draws the conclusions.

II. Fault Types

As shown in Table I, types of faults in LIBs include BMS malfunction, ISC, ESC, sensor, insulation destruction, electrical connection (EC) faults, TR, and contactor fault [38].

TABLE I
TYPES, REASONS, AND HAZARDS OF FAULTS IN LIBSS

Fault types	Reasons	Fault hazards	Fault characteristics	Diagnosis methods	References
BMS malfunction	Hash operation environment	LIBSs breaking down	Communication, decision and action failure	Machine learning-based, knowledge-based methods	[39], [40]
ISC fault	Impure material, imprecise manufacturing, extrusion, puncture, dropping	Increase of voltage inconsistency, rapid degradation, rapid rise of temperature, TR	Voltage drop, temperature rise, joule heat source inside the cell	Model-based, data processing-based, machine learning-based methods	[41]–[43]
ESC fault	Collision, electrolyte leakage, water immersion, connection wire accidental colliding	Temperature rising, aggravated inconsistency, accelerated aging	Voltage drop, temperature rise, joule heat source outside the cell	Model-based and machine learning-based methods	[44], [45]
TR	Rapid heat generation caused by ISC, ESC et al., slow heat dissipation	Battery fire and explosion	Tremendous heat release, venting explosive and flammable gases	Model-based and data processing based and machine learning-based methods	[46]–[48]
Sensor fault	Inherent defects, sensors aging, and harsh working environment	Overcharging and overdischarging protection loss, low precision of state estimation, power protection loss, aggravated inconsistency	Measurement value bias, drift, freezing or scaling	Model-based, and machine learning-based methods	[34], [49]
Insulation destruction	Electrolyte leakage, insulation layer rupture, high voltage wire bonding with shell, abrasion, isolation failure in BMS	Increasing of risk of ESC and electric shock	Insulation resistance dropping	Direct measurement method, electric bridge based method, signal injection based method	[50], [51]
EC fault	Oxidation at the contact surface, poor assembling, and intense vibration	Reduction in the available capacity, aggravated Inconsistency, excessive heat generation	Contact resistance increasing, temperature rise	Model-based, and machine learning-based methods	[52]
Contactor fault	Aging of contactor, hash operation environment	Loss of function, failure of batteries protection, failure of temperature control	Action failure	signal driven-based methods	[53]

A. BMS Malfunction

A BMS is the core device for implementing status monitoring and safety management of LIBs. To reduce the impact of high current, high and low temperature, overcharge and overdischarge on batteries, the use of a BMS is essential. It detects the cell voltage, cell temperature, charge, and discharge current in real time, estimates the state of charge (SOC) [54], state of power (SOP) [55] and state of health (SOH) [56] according to the measured information, and requests appropriate charging voltage and current from the charger. An LIB must be operated within a strict scope [57], so when the cell voltage, temperature and real-time power exceed the normal range, the BMS will transmit a power limit command or cut off the battery pack for its protection. In general, proper monitor and control strategies of a BMS can avoid battery overcurrent, over-temperature, under-temperature, overcharge and overdischarge. However, because of the harsh temperature, humidity, vibration, and electromagnetic environment, BMS may have functional failures, including communication, decision and action failures, which can lead to EV breaking down and ESS tripping. The schematic diagram of a BMS is shown in Fig. 2.

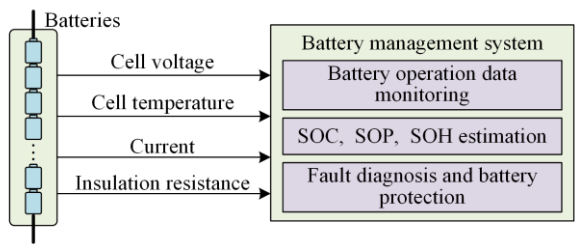

Fig. 2. The schematic diagram of BMS.

B. ISC Faults

ISC is one of the most dangerous battery faults, resulting from the discharge circuit formed by the connection between positive current collector and anode active material within the battery. When the fault degree is minor, the short circuit current will be small so it is difficult to detect and diagnose the ISC. As time goes on, the ISC will increase the voltage inconsistency within the battery pack and finally result in a rapid degradation of the faulty battery. When the fault degree is serious, a large amount of energy will be released in a short time, which will cause a rapid temperature rise inside the faulty battery. After a short time, the high temperature will spread to adjacent batteries, eventually leading to serious safety accidents, such as TR, further fires, and explosions [58], [59].

The causes of ISC are usually divided into two types, i.e., internal and external. In the internal type, impure material and imprecise manufacturing may cause ISC during long-time use. In addition, high current abuse at high temperature will cause lithium dendrite growth, which produces a serious potential hazard of forming an ISC. In the external type, battery extrusion and puncture can cause ISC directly. The schematic diagram of lithium dendrite growth is shown in Fig. 3, and the causes and hazards of ISC are shown in Fig. 4.

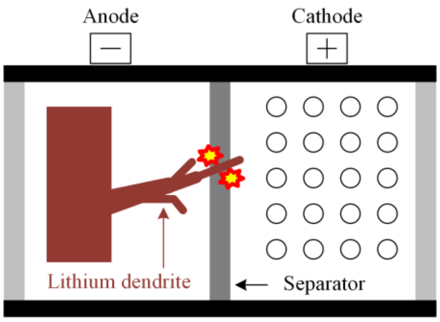

Fig. 3. The schematic diagram of lithium dendrite growth.

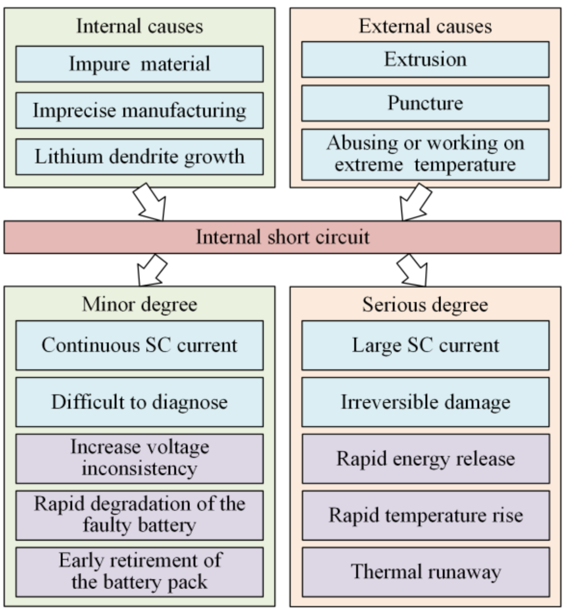

Fig. 4. The causes and hazards of an ISC.

C. ESC Faults

An ESC has a relatively simple mechanism, including deformation caused by collision, water immersion, electrolyte leakage and connection wires accidentally colliding. When an ESC occurs, the energy stored in the battery is released in the form of heat, which increases the temperature of the connection point and subsequently heats up the battery. The rapid heating of the connection point may cause the metal to melt or bounce, thus disconnecting the ESC branch and resolving the ESC fault. Otherwise, the ESC branch will continuously discharge the faulty battery. In the long run, the battery inconsistency will be aggravated and the faulty battery will age at an accelerated rate because of the continuous improper discharging. The warming of the faulty battery is more obvious when there is a high SOC and large short circuit current. The length of the ESC has a great influence on the battery. The longer the short circuit lasts, the more serious the damage to the faulty battery. Prolonged ESC will cause irreversible damage, whereas if the ESC is resolved quickly, the terminal voltage of the faulty battery will be restored. Therefore, accurate and fast diagnosis is important. The causes, automatic resolution and hazards of ESC are shown in Fig. 5.

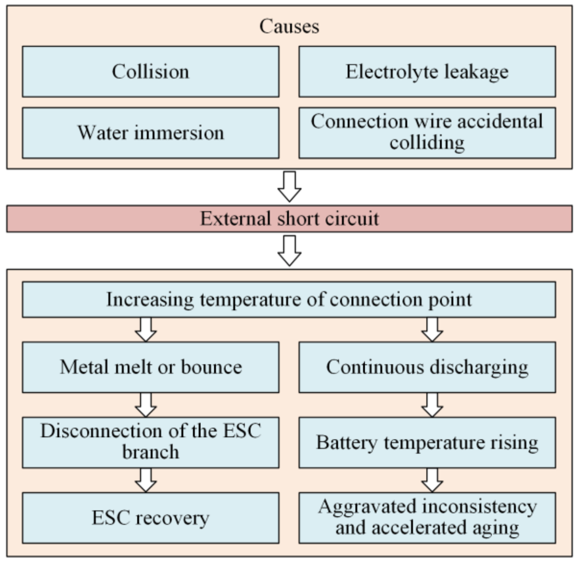

Fig. 5. The causes and hazards of an ESC.

D. TR

TR is the ultimate manifestation of a serious electrochemical fault, accompanied by violent fires and explosions. In TR, one or more batteries heat up quickly and burn, causing the surrounding batteries to burn as well. It often results in the scrapping of the entire EV and the destruction of the entire ESS plant, with potential injures to personnel. Temperature plays an important role in the battery thermal diffusion mechanism [60], and the direct reason for and stimulation of TR are overheating [61]. The main causes of temperature out of control are the increase of heating power caused by an ISC and the low speed of heat dissipation caused by battery abuse at high ambient temperature. Battery usage at high temperature can be attributed to inappropriate management strategies from the BMS. The schematic diagram of a TR is shown in Fig. 6. The features of a TR include severe high internal temperature, large temperature difference within the battery, and significant rise in internal resistance [62], [63]. TR propagation within a LIB system is more serious than the TR in a single cell. The TR propagation is related to different cell types and electrical configurations [64]. Some measures can be taken to delay or prevent TR, such as enhancing the heat dissipation level, increasing the TR triggering temperature, adding an extra thermal resistant layer between adjacent battery cells and so on [65].

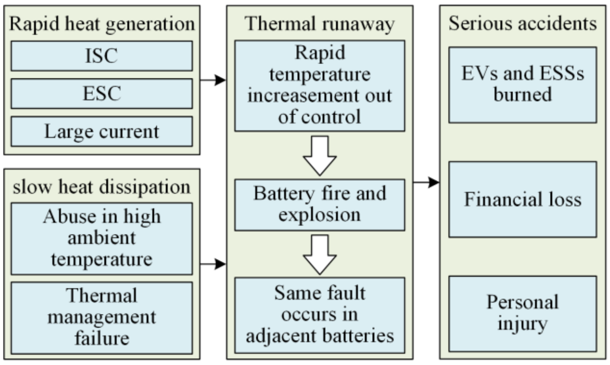

Fig. 6. The schematic diagram of thermal runaway.

E. Sensor Faults

Sensors provide primary battery data for the BMS [66], [67]. Accurate sensing data is the basis of BMS for state estimation and fault diagnosis. In practical applications, sensors will have faults such as volatility, offset, sticking and low precision, due to the inherent defects, aging, and harsh working environment. The data volatility often occurs in a harsh electromagnetic environment caused by power electronic devices, such as motor controllers, power conversion systems, etc. The data sticking is often caused by incomplete sensor status control or wrong data processing, as well as the failure of the sensor itself. Low precision is often caused by inherent problems, such as design and manufacturing defects, and the impact of a harsh environment.

Wrong sensing data can cause the BMS to make a wrong decision, which will accelerate the degradation of batteries and even lead to serious accidents [68], [69]. There are voltage, current and temperature sensors in LIBSs. In the event of voltage sensor fault, a BMS cannot protect the batteries from overcharging and overdischarging, and the inconsistency of multi-cluster LIBSs will be aggravated, whereas faults in the current sensor can prevent BMS from accurately estimating the SOC and performing power protection [70], [71]. When the temperature sensor fault occurs, BMS is unable to perform thermal management, and neither can the maximum acceptable power be accurately estimated. The causes, types and hazards of sensor faults are shown in Fig. 7.

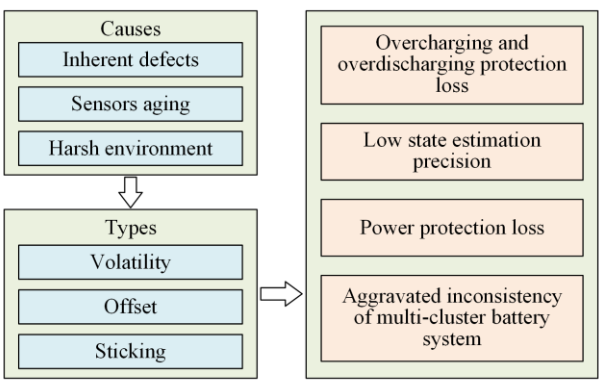

Fig. 7. The schematic diagram of sensor faults.

In addition, as LIBS scale continues to increase, the topology of sensor networks is also constantly improving. In large LIBSs (such as ESSs), the large numbers of batteries bring complexity in wiring arrangement and assembling. In order to improve manufacturing efficiency and reduce the error rate, wireless sensor networks (WSNs), as schematically shown in Fig. 8, are widely used. However, the WSNs sensors are often prone to various faults such as frequent crashes and temporary or permanent failures in harsh environments [72]. Therefore, the rapid configuration, fault diagnosis and recovery of WSNs have become a hot research topic.

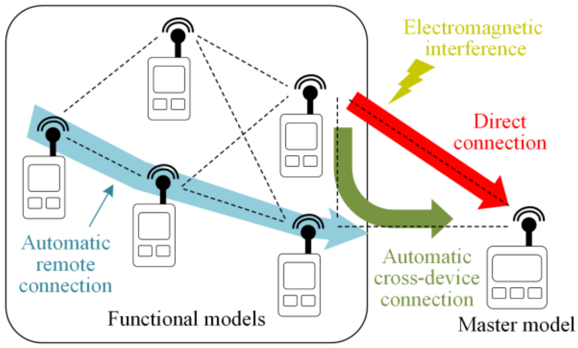

Fig. 8. The schematic diagram of WSNs.

F. Insulation Destruction

At present, the voltages of electrochemical ESSs and EVs have reached 1500 V and 900 V. These require detection of electrical insulation between the shell and two poles of battery pack for safety reasons. The damage of insulation increases the risk of an ESC and electric shock. The insulation degree of LIBSs can be expressed by the equivalent resistance between the shell and two poles of the battery pack. If the equivalent resistance drops below the alarm threshold, it indicates that the insulation of the LIBSs has been damaged. Insulation destruction is mainly caused by electrolyte leakage, insulation layer break, high voltage wire bonding with shell, abrasion due to vibration and isolation failure in the BMS. In dry conditions, the equivalent insulation resistance of newly produced battery packs often reaches 50 MΩ.

The methods of insulation fault diagnosis mainly include direct measurement [73], electric bridge-based including balanced bridge and unbalanced bridge [74], [75], and signal injection based methods [76]. The signal injection method injects voltage or current signal into the battery pack. This can generate a feedback signal for calculating the insulation resistance. To better deal with system noise and improve the accuracy of the calculation results, the signal injection method can combine with the filtering algorithms [77], [78] and adaptive forgetting factor recursive least square (AFFRLS) algorithms [51]. The unbalanced bridge method has high accuracy and low implementation difficulty, but it needs two voltages of the same point with different switch states. Hence, in practical applications, when the current is high, the accuracy is reduced because of the continuous change of terminal voltage of the battery pack. On the other hand, the distributed capacitances between the buses and shells extend the transition time of the voltage to be measured. Once the transition time exceeds the detection period, the accuracy will be greatly reduced. Thus, eliminating the impact of distributed capacitances is a technical focus of BMSs. The causes and implementation methods of insulation destruction are shown in Fig. 9.

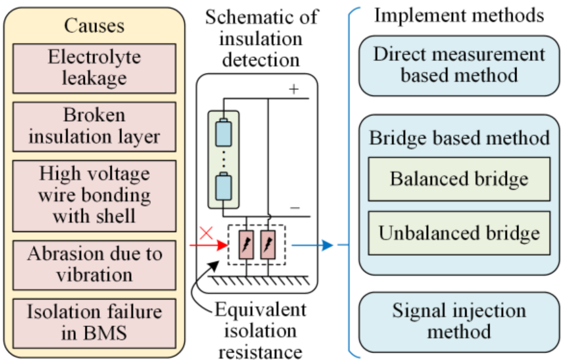

Fig. 9. The causes of insulation destruction and implementation methods of insulation detection.

G. Electrical Connection Faults

An EC fault is a phenomenon in which the connection between the metal connector and the battery pole is weak. This is often caused by oxidation at the contact surface, poor assembling, and intense vibration. When the fault occurs, the equivalent resistance between two neighboring batteries is unstable, thus reducing the dynamic performance of the battery pack [79], [80], and generating excessive heat which will raise the battery temperature [81]–[83]. Prolonged operation under heavy load may lead to melting of metal battery terminals [84]. In the parallel battery structure, poor connection of a single cell will lead to a reduction in the available capacity of the battery, and aggravate the inconsistency within the battery pack. The causes and hazards of an EC fault are shown in Fig. 10.

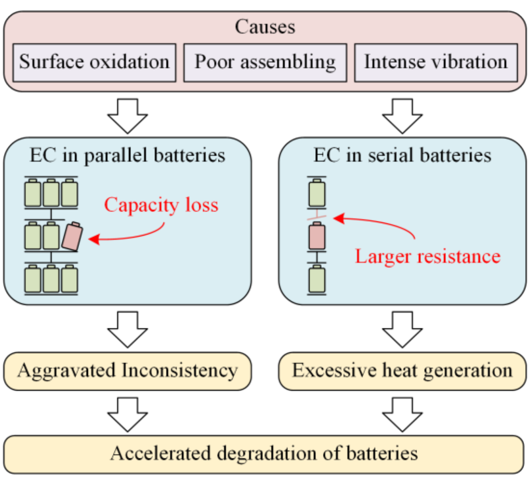

Fig. 10. The causes and hazards of an EC fault.

H. Contactor Faults

Contactor failure can be divided into contactor adhesion and contactor failures. Contactor failure often results in a loss of function or a car breaking down, whereas contactor adhesion can result in the failure to protect batteries or control temperature, potentially leading to more serious accidents. To detect whether the action of the contactor is consistent with the driving signal, many contactors are usually equipped with auxiliary contactors, so that the BMS can detect the signals of auxiliary contactors to determine the state of the contactor. However, this detection method is invalid when the auxiliary contactors have the same failure as the primary contactor.

III. Fault Diagnosis Methods

As shown in Fig. 11, the fault diagnosis methods can be roughly classified into four categories, i.e., model-based [85], data processing-based [86], machine learning-based [87], and knowledge-based methods [88].

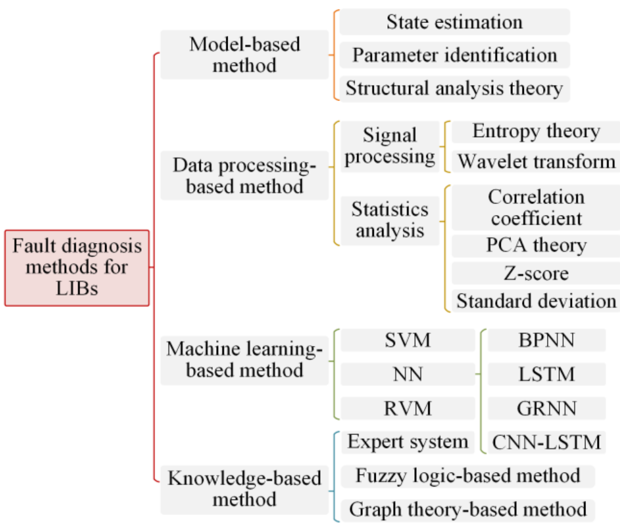

Fig. 11. Fault diagnosis methods for LIBs.

A. Model-based Methods

Model-based fault diagnosis methods employ the battery model to generate a set of residuals by comparing the signals from the model with the measurable signals to obtain fault information. The residuals are then evaluated by fault thresholds to judge whether the LIBS is at fault. Battery models, including electrical, thermal and coupling models, are the basis for model-based fault diagnosis methods. In theory, the residual values are zero when the LIBS has no fault, and when a fault occurs the residuals will deviate from its normal range. However, the residual values fluctuate around zero even with no battery fault because of modeling errors and the impact of measurement noise and process noise on the actual system. Model-based fault diagnosis methods can be divided into categories of parameter estimation, state estimation, and structural analysis [89].

The state estimation method uses filters such as Kalman filter (KF) [90], extended Kalman filter(EKF) [91], unscented Kalman filter (UKF) [85], and particle filters filter (PF) [92], or observers such as sliding mode [71], Luenberger [93], and adaptive observers [94], to reconstruct or estimate state parameters, including SOC, open circuit voltage (OCV), terminal voltage, etc., from the established battery models, and then generates residuals by comparing them with measured values. The commonly used battery models include equivalent circuit (ECMs) [95], electrochemical [96], coupling (electric-thermal coupled [97], [98], electrochemical-thermal coupled [99], mechanical electrochemical-thermal coupled [100]), and fractional order models (FOMs) [101]. The state estimation method can achieve real-time fault diagnosis, while simultaneously monitoring the states of the LIBS.

Faults can affect the physical characteristics of the LIBS, leading to changes in model parameters. Parameter identification methods estimate parameters that can reflect the physical characteristics of the LIBS, and fault diagnosis is conducted through parameter changes before and after the faults. Because of the strong non-linearity of the LIBS, nonlinear parameter estimation methods such as least squares [102], filtering techniques, and genetic algorithms (GAs) are used to estimate system parameters. However, the parameter identification method requires a high-precision battery model to accurately estimate battery parameters.

The structural analysis finds the structural over-determined part of the system model by analyzing the system structural model. Then a residual is generated based on the structural over-determined part for fault diagnosis. The structural analysis method can analyze the process of fault detection and isolation (FDI). This facilitates the design of residual generation for fault isolation [103].

B. Data Processing-based Methods

When a fault occurs in the LIBS, fault information will be contained in the data collected by the sensors. Therefore, LIBS fault diagnosis can be carried out by analyzing measurement data. The data processing-based method employs some signal processing techniques and statistics analysis methods [104], such as Shannon entropy [84], sample entropy [105], wavelet transform [106], standard deviation [107], correlation coefficient theory [86], Z-score [108], principal component analysis (PCA) [109], [110] and so on, to perform special data processing on measured data, in order to extract effective fault features for fault diagnosis. As data processing-based methods depend on neither precise analytical battery models nor the experience of experts, nor understanding of the complex system structure and fault mechanism, they have been widely applied to LIBS fault diagnostics.

C. Machine Learning-based Methods

Machine learning-based methods learn knowledge from training sample sets for fault diagnosis. Neural networks (NNs) and the support vector machine (SVM) [111] are two typical machine learning algorithms for fault diagnosis for LIBSs.

NNs include the back-propagation neural networks (BPNN)[97], long short-term memory (LSTM) [87], [112]–[114], general regression neural networks (GRNN), and convolutional neural networks (CNN)-LSTM [115]. The principle of fault diagnosis based on an NN is to establish the inference relationship between fault data and fault types through training. Then, in the online diagnosis stage, the real-time collected battery data serves as the input to the NN and its output is the possible types of faults in the LIBS. This method requires a large amount of accurate fault data to train the network, otherwise it may lead to over-fitting, which can result in reduced accuracy.

The principle of fault diagnosis based on an SVM is to map the input space to the high-dimensional space through the kernel function, and find the optimal hyperplane in the high-dimensional space. This method treats fault diagnosis as a sample classification problem and trains accurate classifiers based on historical data for fault diagnosis. Compared with an NN, an SVM has better generalizability and is more suitable for LIBSs because of its limited data.

The relevance vector machine (RVM) is a sparse probability model, which is a supervised learning approach and is carried out in a Bayesian framework. Compared to the SVM algorithm, the RVM has many advantages, including higher sparsity, simpler parameter setting, and the kernel function is not restricted by Mercer condition. Also, it can give the posterior probability of class memberships to provide a better judgement for fault diagnosis [116].

D. Knowledge-based Methods

The knowledge-based methods use the knowledge of fault diagnosis, without relying on the mathematical model of the battery, though they require a thorough understanding of fault mechanisms in advance. The widely used knowledge-based fault diagnosis methods include expert systems [117], fuzzy logic-based [88], and graph theory-based methods [118].

The expert systems simulate the reasoning and decision-making of experts in related fields, using historical databases and the rich experience and knowledge of experts to establish knowledge and rules. When they are applied to fault diagnosis, there are some problems such as inaccurate knowledge representation and difficulties in acquiring knowledge. The fuzzy logic methods use fuzzy parameters, models, and thresholds to perform fault diagnosis. The graph theory methods use the fault propagation relationships between various components in an LIBS to construct a fault diagnosis network. However, the complex mechanisms make it difficult for them to establish accurate fault diagnostic networks.

IV. Fault Diagnosis

Fault diagnosis can be divided into three subtasks [89], as shown in Table II. Fault detection indicates the discovery of a fault, fault isolation refers to the localization or classification of the fault, while fault identification or analysis refers to determining the cause and magnitude of the fault [119]. At present, a wide variety of schemes and algorithms have been employed for fault diagnostics.

TABLE II
FAULT DIAGNOSIS SUBTASKS

Fault diagnosis sub-task	Meaning
Fault detection	Discovering of a fault
Fault isolation	Localizing or classifying the fault
Fault identification or analysis	Determining the cause and magnitude of the fault

A. ISC Faults

The ISC fault is one of the most serious faults in an LIB system and the fire accidents of EVs are mostly caused by an ISC induced battery TR [120]. The methods used for ISC diagnosis include model-based, data-processing-based, machine learning-based and other diagnosis methods.

1) Model-based Methods

When an ISC fault occurs, the ISC will lead to changes of electrical parameters such as OCV, OCV difference, internal resistance, SOC, SOC difference, and leakage current due to the abnormal loss of cell electricity caused by self-discharging of the ISC [16]. Based on this characteristic criterion of an ISC fault, reference [121] estimates the cell SOC difference with the mean SOC for a battery pack by EKF based on a cell difference model (CDM). A micro-short-circuit (MSC) diagnostic method is then presented by employing a recursive least squares (RLS) filter, which can estimate the short-circuit resistance accurately. The short circuit fault can be detected through checking the difference between the estimated and calculated SOC. Reference [122] constructs an H_∞ nonlinear observer to estimate the SOC and soft short circuit (SC) current based on an augmented state-pace battery model. The soft SC fault is detected by checking the difference between the estimated SOC from the observer and the calculated SOC from Coulomb counting. In [123], an online model-based fault-diagnosis algorithm is presented for an ISC. The algorithm estimates the SOC and Ohmic heat resistance using the EKF and the RLS. Subsequently, the ISC fault and its fault level are determined by the deviations of the SOC, internal ohmic resistance, voltage, and temperature between batteries. Reference [124] presents a model-based switching model method (SMM) to detect an ISC in the LIB. The ISC is introduced into the ECM, while the OCV and SOC are estimated based on the improved ECM using the RLS algorithm. Then, the ISC resistance, and an ISC fault index, are estimated accurately from the estimated OCVs and SOCs to update the model and detect the ISC fault.

References [125] and [126] conduct diagnosis for an ISC fault based on the SOC estimator and ISC resistance estimator using ECM. In order to diagnose an ISC with high diagnostic accuracy as well as strong robustness to battery degradation and disturbance, reference [127] proposes an aging-robust and disturbance-immune ISC diagnostic method incorporating a multistate-fusion ISC resistance estimator and a recursive total least squares with variant forgetting (RTLSVF)-based bias compensator within a universal model-switching framework. In [128], a multi-state fusion-based ISC fault diagnosis method is proposed to estimate the ISC current and resistance via the multi states of batteries.

Reference [129] proposes a three-dimensional electrochemical-thermal model to simulate the ISC fault of an LIB. This makes ISC detection a parameter estimation problem. In this model, the RLS algorithm with a forgetting factor is employed to estimate the crucial parameters in the ECM and the energy balance equation (EBE) model. These are used to detect the ISC. In [130], a mechanical-electrical-thermal modeling approach is presented for predicting the ISC of a lithium-ion cell when the ISC is induced by mechanical abuse.

2) Data Processing Methods

Voltage difference value has a strong correlation with the occurrence of a fault [131]. Reference [120] proposes a cell voltage difference-based method to diagnose an ISC online in the TR process. It is simple and reliable to implement in engineering use. The results suggest that the ISC is the main cause of TR, while overcharge is also a potential cause. In [132], a mutual information-based micro short circuit (MSC) fault detection method is proposed, one which can distinguish the MSC fault from low capacity because MSC is more time-related than that of the low capacity. In [133], an empirical mode decomposition and sample entropy based ISC diagnosis scheme is presented, where empirical mode decomposition is employed to extract the effective fault features from battery terminal voltages.

These are then used to calculate the sample entropy values. Reference [134] also adopts the Shannon entropy algorithm for detecting the early stage of an ISC, while [135] presents a voltage correlation coefficient-based fault detection method for short circuits. This applies a moving average window to improve the detection sensitivity to detect the MSC faults, and an additive square wave is designed to avoid misdiagnosis. It proves that the inconsistency of batteries has little effect on the robustness of this method. Another study in [136] employs the new mean-normalization to amplify the voltage characteristics of the ISC cell. This reduces the amount of data and computation. In [137], a local gravitation outlier-based fault diagnostic method is presented for serial lithium-ion batteries. It extracts fault characteristics from the variation trend of battery voltages.

3) Machine Learning-based Methods

Reference [138] proposes a random forest (RF) classifier-based real-time ISC detection method. The RF classifier is trained with a dataset generated with and without an external short-circuit resistance across the battery terminals. The test experiment shows that the accuracy of the RF classifier is over 97%. In [139], a large database of battery tests is obtained by using a cell high-accuracy finite element model to produce over 2500 numerical simulations. Based on the machine learning results, a classifier that can quickly predict the ISC fault is developed. Combined with multiple factors of a single time step input generation algorithm and the single factor at multiple time steps input generation algorithm, the local outlier factor (LOF) method is adopted in [140] to diagnose battery faults for ESS. The method is validated in two cooling conditions, and the results show that the method can detect the faulty cell at ISC severe levels of $1\ \Omega$, $10\ \Omega$ and $100\ \Omega$ in the air-cooled LIB ESS and two faulty cells at ISC severe levels of $100\ \Omega$ and $25\ \Omega$ in water-cooled LIB ESS.

4) Other Diagnosis Methods

Reference [141] proposes an incremental capacity curve-based ISC diagnosis method to detect the leakage current by the area difference between the normal cell and the ISC cell, and to calculate the ISC resistance. A quantitative diagnosis method is proposed in [142] for a single LIB by comparing the discharge and charge capacities with normal values, whereas [143] presents a remaining charge capacity (RCC)-based MSC fault diagnosis method. This obtains the MSC resistance by analyzing the charging cell voltage curve (CCVC) horizontal transformation.

Reference [144] proposes a self-discharge detection-based MSC detection method, where the current profile resulting from the potentiation polarization enables the precise determination of self-discharge. In [145]–[147], a symmetrical loop circuit topology (SLCT)-based ISC detection method is proposed to identify the ratio and sign of the short circuit currents in parallel connected batteries, while time performance improvement of hours to seconds and good sampling accuracy under dynamic conditions are validated. Reference [148] proposes an early ISC fault diagnosis scheme using generalized dimensionless indicators (GDI) and LOF algorithms for LIB packs. This maps fault indicators to a 2-dimensional space through parallel moving windows. An impedance identification approach is proposed in [149] for micro ISC diagnosis in an LIB cell, and it validates that ISC faults can be detected through the impedance difference between the normal and faulty cells, where the impedance gradually increases as the degree of the short circuit increases. Reference [150] presents a beam model approach-based method according to the positive and radial deformation for the ISC prediction, while [151] presents two ISC criteria according to the separator failure, i.e., the stress state-based criterion for comprehensive detection, and the strain state-based criterion for easy operation. Reference [152] presents volumetric and equivalent strain-based ISC criteria for two representative fault modes, i.e., rapid, and gentle voltage drop. This is applicable for multi mechanical loadings.

B. ESC Faults

The results of an ESC include harness damage, shell deformation and maloperation. These will increase the inconsistency and accelerate the aging of LIBs.

1) Model-based Methods

Reference [153] establishes a two-step ECM to describe the ESC process and proposes an online model-based scheme to diagnosis the ESC fault, achieving accurate and rapid diagnosis of battery packs. In [154], a two-layer model-based ESC fault diagnosis algorithm is proposed to recognize the battery and give a precise model-based diagnosis. It employs an improved first-order RC model and a dynamic-neighborhood particle swarm optimization (PSO) algorithm, and achieves a fast diagnosis, i.e. within 5 s. As shown in Fig. 12, reference [155] presents a FOM and RF model-based three-steps online diagnosis algorithm to identify the ESC fault and electrolyte leakage of the LIB by calculating the root mean square error (RMSE), where the parameters of FOM are identified by the GA and the pre-trained RF model uses the values of discharge capacity, with maximum temperature increase used to improve robustness.

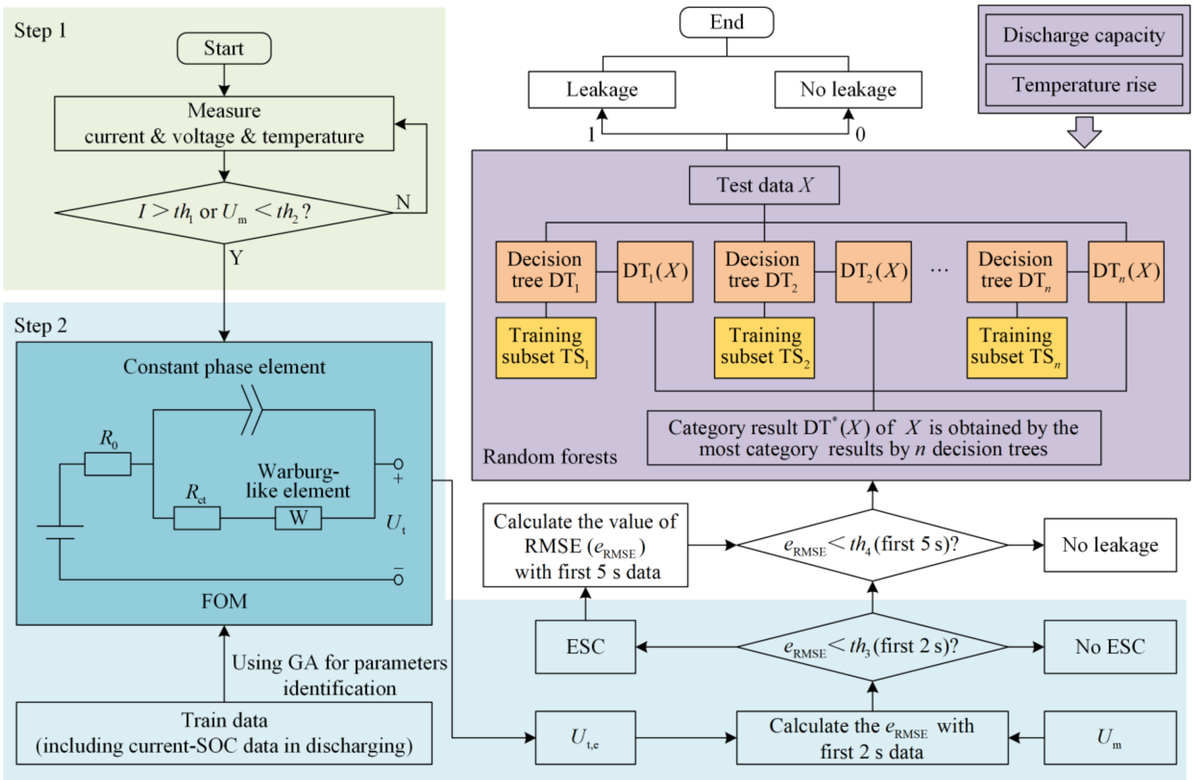

Fig. 12. Framework of ESC fault diagnosis scheme.

Reference [156] proposes a modified dual EKF-based diagnostic method for the external soft-short circuit (SSC), achieving accurate and fast diagnosis in one cycle.

2) Machine Learning-based Methods

Reference [157] proposes an SVM-based and two-step prediction approach to diagnose ESC faults. It predicts the LIB maximum temperature rise, whereas reference [158] presents a supervised statistical learning algorithm-based and model-free method to diagnose ESC faults using a Gaussian classifier.

C. EC Faults

A variety of factors such as installation defects, frequent vibrations, bumps, or shocks can cause bolts and welds to loosen. These factors and oxidation of the metal surface are the causes of EC faults. EC faults increase the inconsistency of parallel batteries, and reduces the available capacity of the whole group. It will also cause the battery pack performance to decrease and affect the battery life.

1) Model-based and Data Processing-based Methods

Reference [159] presents a connection fault diagnosis method for a series battery pack based on the first-order RC ECM and the least squares method. It analyzes both the battery internal resistance and its abnormal fluctuation. Reference [160] presents a connection fault detection scheme of series-connected lithium-ion batteries packs by identifying the abnormal voltage states by the mean square error of voltage, which increases when the temperature changes. A Shannon entropy-based EC fault diagnosis scheme is proposed in [161] for an LIB pack. It captures the unstable characteristics of the contact resistance to diagnose the EC fault. Reference [84] proposes an entropy-based EC fault detection method. This adopts an optimal filtering method combined with a discrete cosine filter method to characterize the system noise according to the vibration frequency to predict the accurate time and location of electrical connection faults in real time. In [162], Shannon entropy is used to process the cell-measured voltage data which is denoised by wavelet transformation to accurately detect the battery connection fault. Compared with the method in [84], this method simplifies the calculation and has lower requirements for hardware.

2) Machine Learning-based Methods

In the production process of laser welding batteries, visual inspection usually occurs. Common visual inspection fails to succeed in both reliability and computational efficiency. Reference [163] proposes a deep learning-based method, and builds a welding spot quality inspection dataset connecting with a real assembly line, and takes less than 100 ms when implementing in Nvidia 1060 and Intel i7-6700. In [164], EC faults in parallel battery packs are diagnosed according to the current distribution, and a LSTM network is developed to predict the unmeasured current distribution from easily collected information.

3) Other Diagnosis Methods

In many possible faults of the series-parallel connected LIB pack, the cell open circuit (COC) fault is one of the causes that leads to strong inconsistency in the pack and the decline of pack life. Reference [165] proposes five COC fault real-time diagnosis methods for the series and parallel connected LIB pack, i.e., Kirchhoff's law-based, Pearson correlation coefficient-based, short-time Fourier transform based, LSTM and recurrent neural network (RNN)-based, and dual extended Kalman filter (DEKF) based methods. These diagnosis methods only rely on pack current and terminal voltages of modules. The test results indicate that the Kirchhoff's law-based method has the shortest diagnostic delay, lowest computational cost, and lowest misdiagnosis rate, and is more applicable for online COC fault diagnosis. Reference [166] investigates the energy loss caused by the EC resistances at the current-collector bars and interface of electrodes, and in LIB assemblies for the first time.

D. Sensor Faults

Accurate estimation of internal states of an LIB is critical for the reliable and safe operation of EVs. At present, the states estimation algorithms have been widely researched, and can be divided into model-based and data-driven methods. The prerequisite of these methods to achieve accurate estimation is normal operation of sensors. For data-driven state estimation methods, if training data include inaccurate data from faulty sensors, the trained state estimation model may be inaccurate and unreliable. Even if the pre-saved model is accurate, they still cannot estimate states precisely if sensors malfunction when this estimation model is applied online. As for model-based methods, sensor faults will lead to reduction of accuracy of state estimation. Therefore, sensor faults need to be profoundly studied to help ensure the accurate estimation of LIB states [167].

1) Model-based Methods

Reference [168] presents a model-based sensor FDI scheme for lithium-ion batteries considering battery degradation. It estimates the ECM parameters in real time. In [169], a structural analysis-based scheme is proposed to detect and isolate sensor faults of an LIB pack using a sequential residual generator, while [170] designs a nonlinear parity equation residual generation (NPERG)-based scheme to detect and isolate sensor faults, with the assumptions that the subset of inputs and outputs is non-faulty and is the signature of the residuals. Reference [70] proposes an EKF-based systematic fault diagnosis scheme for current or voltage sensor faults, where the residual is generated by comparing the measured and estimated voltage, achieving good noise robustness.

However, it is very difficult to determine the process noise covariance in real applications, while an inaccurate process noise covariance matrix will degrade fault diagnosis performance. To address this issue, references [171], [172] propose an adaptive extended Kalman filter (AEKF)-based improved sensor faults diagnosis method for LIB packs. This adjusts the measurement and process noise covariance adaptively and determines the noise covariance. Reference [71] presents a model-based current, voltage, temperature sensor diagnostic method which employs three sliding mode observers based on the electrical and thermal dynamics of the LIB. As shown in Fig. 13, a model- based current, voltage sensor FDI method is developed for a series-connected lithium battery pack, where the true SOC is calculated by Coulomb counting and the estimated SOC is obtained by the UKF and RLS joint estimation method [173].

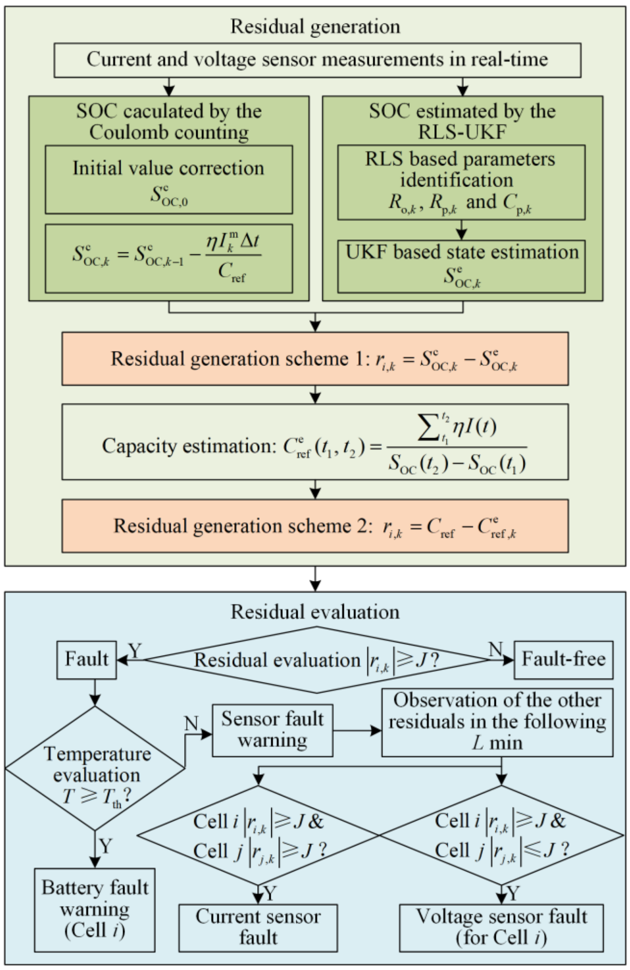

Fig. 13. Sensor fault detection and isolation scheme.

Reference [174] presents a structural analysis and EKF-based fusion sensor fault diagnosis method, which derives the minimally structural over-determined (MSO) sets and addresses the issue of inaccurate initial SOC in the MSO, to diagnose the faulty sensors by evaluating the residuals. In [175], a new and fast model-based sensor fault diagnosis method is proposed for LIB packs, using a predefined factors, EKF and multiple model adaptive estimation scheme. Reference [176] proposes a hybrid system-based sensor fault diagnosis scheme for LIB packs. This adopts distributed diagnostic structures to reduce computational complexity. Current sensor fault diagnosis can prevent over-charge and over-discharge. Inspired by this, reference [177] adapts a PSO-based model to estimate the load current by analyzing the residuals with the Monte-Carlo method to generate an empirical residual threshold, which is robust to modeling uncertainties and voltage measurement noise.

2) Machine Learning-based Methods

Voltage abnormality always implies one or more faults in batteries. However, voltages of faulty cells often do not exceed the safety threshold before a fault occurs. Therefore, it is important to accurately diagnose a voltage fault in the entire operation process of EVs in a timely fashion to prevent severe damage of batteries. Reference [178] proposes a high frequency sampling-based method to diagnosis sensor faults, and four neural network-based voltage prediction models are developed for the four kinds of driving conditions respectively, achieving good voltage prediction and fault diagnosis in various conditions.

3) Other Diagnosis Methods

Reference [72] designs a self-adaptive-based autonomous fault-awareness (SAAFA) model to limit the impact of WSN crashes and failures, and filter the signals for gaining pure measures free of interference. It improves the robustness of the WSN, which makes it convenient for wide-scale application in a harsh environment. Combined with an improved sensor topology, references [179] and [180] propose an improved interleaved voltage measurement method according to a graphical interpretation visualizing the co-prime constraint. This has a broader application and lower noise level. In [181] and [182], a multi-fault diagnostic method is proposed, one which uses correlation coefficient theory and interleaved voltage measurement topology, as shown in Fig. 14, correlating each cell and contact resistance with two different sensors respectively, with high robustness and sensitivity.

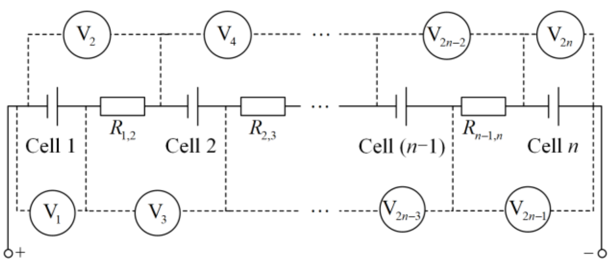

Fig. 14. Interleaved voltage measurement topology.

E. Thermal Faults

The main phenomena of TR include the LIB rapidly heating up and eventually exploding[183]–[185]. They are mainly caused by battery aging, overcharge, and high temperature operation.

1) Model-based Methods

References [38] and [169] present a structural analysis and sequential residual generation-based cooling system FDI scheme, which establishes a structural model to analyze the detectability of the faults, and uses the minimal structurally over-determined part to generate sequential residuals. In [186], an electrothermal coupling model based thermal fault diagnosis algorithm is presented to diagnose a heat generation fault and thermal parameter fault in cylindrical lithium-ion batteries. As shown in Fig. 15, a Lyapunov-based observer [186] is designed to estimate internal resistance, and the KF-based observer is proposed to estimate both surface and core temperatures, while an adaptive threshold is adopted to suppress modeling and measurement uncertainties.

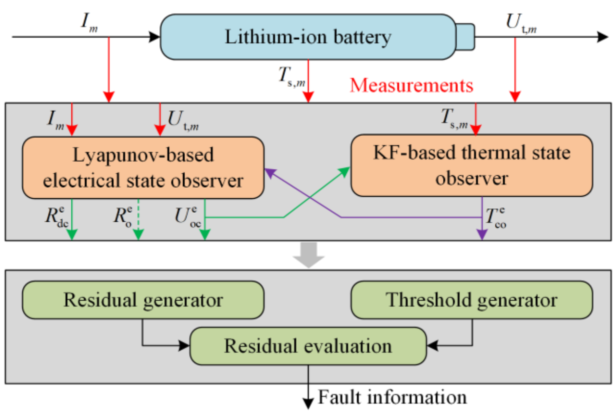

Fig. 15. Thermal fault diagnosis algorithm.

Reference [187] proposes a partial differential equation (PDE) model-based real-time thermal faults diagnosis scheme for LIBs, using a distributed parameter 1-D thermal model of cylindrical battery cells and a PDE observer. A two-state thermal model-based diagnostic algorithm for thermal fault diagnosis in LIBs is presented [188], which describes the dynamics of the surface and core temperatures of a battery cell, while considering and suppressing the modelling uncertainties by designing an adaptive threshold generator. Reference [170] uses the nonlinear parity equation method, which describes the fault diagnosis problem to detect and isolate cooling system faults.

2) Machine Learning-based Methods

Reference [189] proposes a neural network-based approach to detect thermal faults of lithium-ion batteries. It uses a long short-term model based neutral network model in conjunction with the stretch-forward technique to estimate the surface temperature of cells and detect the thermal faults with high accuracy. In [190], an online diagnosis method of TR for lithium-ion batteries is proposed. This is based on the density-based spatial clustering of applications with noise clustering to evaluate the fault risk of cells and diagnose the potential TR cells according to real-world data. It can accurately predict the locations of a TR in battery pack a few days before fault occurrence.

3) Data Processing-based Methods

To overcome the difficulties in selecting the calculation window, reference [105] presents a real-scenario-based TR prognosis on a ternary battery, and a determined anomaly coefficients-based real-time multilevel prognosis strategy to improve sensitivity. Reference [191] develops a four-step TR prediction method, and a lumped thermal resistance network is developed using the battery pack's heat transfer characteristics, while the core temperature of the battery is predicted by solving the energy transfer equation using an electrical circuit analogy. In [192], it is found that when the battery is overcharged, its impedance changes at 30−90 Hz. From this discovery, a low-cost and compact device is designed to measure the dynamic impedance during the overcharge process to detect an overcharge predicted TR.

F. Battery Degradation

Battery degradation is accompanied by various phenomena, such as capacity abnormality, aggravation of inconsistency, and power fade. Therefore, the monitoring of the above phenomena is necessary in the detection of battery aging.

1) Model-based Methods

Reference [193] proposes an historically independent algorithm for online direct current resistance detection, one which adopts FOM and RLS identification with virtual current design. In [194], a low-cost, computationally small, SOC-insensitive multi-point impedance model is proposed to monitor aging of LIBs by estimating the ohmic and contact resistance.

2) Data Processing-based Methods

In order to reduce the cost of battery energy storage, research on the second-use application of retired batteries has become attractive. Considering the serious potential insecurity of retired batteries, potential hazards should be diagnosed in advance in battery tests. Overcharging and overdischarging are the two main reasons for accelerated battery degradation. Reference [195] develops a fast diagnostic method for an accelerated degradation fault, and detects the unusual changes in the back-end voltage and calculates its second-order derivative after being normalized to recognize the accelerated degradation fault even if the historical data is lost because of its less stringent data requirement. Reference [196] uses PCA for the capacity degradation diagnosis of the battery for ESSs, while [161] proposes a power fade fault diagnosis method, demonstrated in an EV with 96 cells in series. This study shows that the power fade fault is caused by the internal or contact resistance increase. This diagnosis method uses Shannon entropy to identify the cause of the power fade fault, while appropriate measures are taken to remove the fault.

3) Machine Learning-based Methods

As a key indicator of the charging process, charging capacity can represent the SOH of a battery system. Abnormal charging capacity may result in sudden changes of SOC, which, in turn, could give rise to severe safety issues. As such, charging capacity diagnosis is necessary for safe operation. Reference [197] proposes a machine learning-based prediction framework for battery charging capacity diagnosis. This uses massive real-world EV operating data. The impedance and capacity inconsistencies among the parallel-connected batteries can lead to uneven current distribution, which can further result in accelerated aging and safety issues. Thus, reference [87] uses the current and voltage values of every parallel battery pack to estimate the uneven current distribution via RNN with LSTM, and finally achieves the inconsistency diagnosis. This method can accurately track the trend and abnormal rise of branch currents in multi-parallel battery packs and achieve inconsistency diagnosis.

G. Multi Faults

Different types of faults may have similar effects on the thermal and electrical characteristics of an LIB. False diagnosis may occur if only one individual type of fault is researched. Therefore, it is necessary to research diagnosis methods that simultaneously consider multiple faults in LIBs.

1) Model-based Methods

Reference [198] uses multiple nonlinear models representing signature faults to achieve effective diagnosis of overcharge and overdischarge faults of LIBs. A residual signal is used in the multiple-model adaptive estimation technique to generate probabilities that determine the signature faults. Reference [199] presents an adaptive unscented Kalman filter-based fault diagnosis method to diagnosis the parameter bias of LIBs in real time, and slow-varying-type faults and abrupt-type faults are taken as cases to be experimentally tested. In [200], an interactive multiple-model (IMM) algorithm-based damage detection method is presented to detect early damage of batteries. A mode probability is calculated from the innovations and covariances of the predicted measurement. This indicates whether a cell is damaged. Reference [201] also proposes an IMM algorithm combined with UKF to diagnose multiple faults of lithium-ion batteries with improved noise suppression capability.

Reference [202] presents a structural model-based multi-fault diagnosis scheme for LIB systems using the structural analysis methodology. The LIB system degree of analytical redundancy is increased by adding a different number and type of sensors, while a software-in-the-loop (SIL) validation approach shows that the proposed method can successfully detect and isolate ISC, ESC and sensor faults in a LIB system.

Reference [176] proposes a multi-fault detection and isolation method for the sensor faults and relay faults of LIB packs based on a hybrid system and DEKF. Hybrid automaton is used to model the battery pack, while a distributed diagnostic structure is adopted to reduce computational complexity. The DEKF algorithm is employed to estimate the model states and parameters. In [203], a hybrid system-based multi-fault diagnosis approach is proposed for an LIB pack, as shown in Fig. 16. This diagnosis method adopts a decentralized diagnostic structure with two local stochastic hybrid automata in order to reduce computational complexity. Battery cell parametric faults are diagnosed and distinguished from sensor faults at the cell level by using parameter identification-based and residual evaluation methods. Sensor faults and relay faults are detected and isolated through an unscented particle filter-based hybrid system mode estimation and discrete event system diagnosis method at the module level. The random multi-fault injection experiments indicate that the mean diagnosis time of cell parametric, sensor and relay faults are within 30 s, 20 s, and 5 s, respectively, while the missed diagnosis rates are within 2% with no false diagnosis.

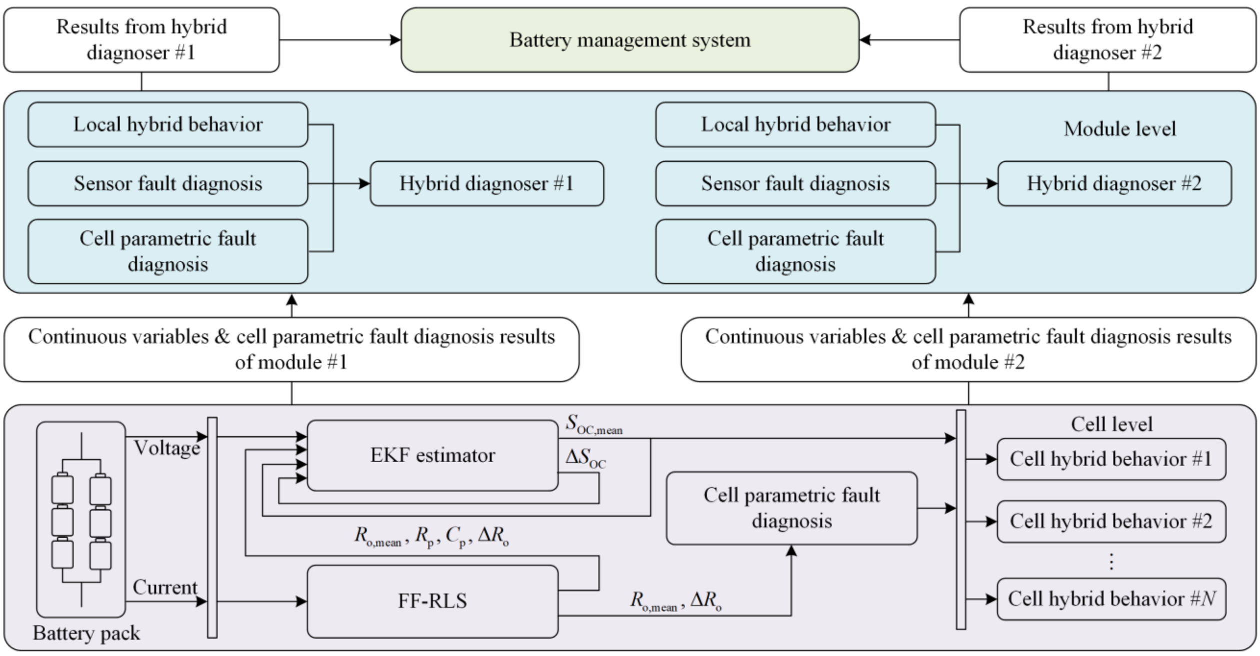

Fig. 16. Structure of the multifault diagnosis approach based on the hybrid system.

2) Data Processing-based Methods

Reference [204] proposes a modified sample entropy-based real-time multi-fault diagnosis method, which can diagnose and predict different early battery faults, including short-circuit and open-circuit faults, and can also predict the time of occurrence of faults. References [205] and [206] adopt a sparse data observers-based method and a modified variance-based method to diagnose the minor faults comprising open circuit and short circuit faults, respectively. The proposed methods have high accuracy, small calculation burden, and model-free characteristics.

Reference [182] presents a multi-fault diagnostic strategy based on interleaved voltage measurement topology and improved correlation coefficient method. The strategy can diagnose and locate several types of faults, i.e., the internal/external short circuit, sensor and connection faults. However, the number of voltage sensors required for this diagnosis scheme is twice the cell number. In [207], another online multi-fault diagnostic scheme based on a non-redundant crossed-style measurement circuit and improved correlation coefficient method is proposed. This can distinguish cell faults from other faults and isolate the connection and voltage sensor faults with high robustness. However, this approach does not consider the effect of cell inconsistency on the correlation coefficient. In contrast, reference [208] considers the effect of inconsistencies in the SOC and resistance on the correlation coefficients. A multi-fault diagnosis method is proposed to detect and isolate short circuit, voltage sensor, and connection faults based on the correlation coefficients and variation in the voltage difference. The results show that the scheme considering inconsistencies can improve the speed and accuracy of diagnosis. Reference [209] uses the interclass correlation coefficient values and the order of cell voltages to identify the failures of battery packs to detect battery anomalies.

Reference [210] presents a big data statistical analysis-based novel fault diagnosis method, which can achieve the verification of the detection results by the LOF and clustering outlier diagnosis algorithms. In order to improve the practicality of fault diagnosis methods, reference [211] proposes one for LIBs in EVs based on the multi-method fusion of big data. In [212], a novel diagnosis and abnormality detection method is investigated for the battery pack of electrical scooters based on statistical distribution of operational data stored in the cloud platform. This method calculates the Gaussian distribution-based diagnosis coefficient to highlight the parameter variation, and then detects and locates the faulty cell in a timely fashion. Reference [213] presents an ISC and sensor fault diagnosis scheme for LIB systems based on multivariate statistical analysis and voltage correlation coefficient. This adopts a novel multi-fault diagnosis logic using an improved contribution plot and cross-cell sensor topology. In addition, a semi-quantitative merit-seeking criterion is proposed. This can determine the optimal window-width by kernel density estimation. The proposed method significantly outperforms existing correlation coefficient-based diagnosis methods in terms of diagnostic intuitiveness, detection latency, and fault detection rate for LIB system fault diagnosis. Reference [214] proposes a novel data-driven method for early-stage battery fault warning by the fusion of short-text mining and the grey correlation, and establishes a fault-prediction model for electric buses based on big data on the key feature variables. This model can effectively predict the faults and carry out the desired early fault warning.

3) Machine Learning-based Methods

Reference [215] adopts a genetic algorithm-based back-propagation neural network (GA-BPNN) method for multi-fault diagnosis of LIB systems. The GA is integrated with the BPNN for initializing and optimizing the connection weights and thresholds. Compared with the BPNN model, the GA-BPNN has better fault diagnosis performance. In [216], a Bayesian network is used to perform fault diagnosis. This uses expert knowledge to create fault nodes. Historical and maintenance record data are employed to establish the built network structure and learn network parameters. The results of the experiments aimed at multi-battery faults show high range accuracy. Reference [217] proposes a fault diagnosis and prognosis method based on a nonlinear auto-regressive exogenous (NARX) neural network and boxplot for the first time. The NARX neural network can accurately predict future battery voltage, while based on the predicted voltage, the boxplot is used for battery fault diagnosis and early warning. Reference [218] proposes a fault diagnosis method based on a multi-classification SVM based on a partial binary tree structure. This approach can decrease the dependence on data volume and improve detection accuracy and training speed. In [219], a state-partitioned voltage fault prognosis method based on a self-attention network is proposed. This can diagnosis multiple faults in new energy vehicle batteries using voltage. Reference [220] presents a vehicle-cloud coordinated multi-type fault diagnostics approach. A battery system simulation model (BSSM) is established based on the simulation experiments of various types of faults to obtain massive charging-discharging cycle data for algorithm training at the cloud end, while feature differences are extracted from the vehicle end by using the cell difference model. Thus, the decision tree classifier with high precision is trained and its parameters are optimized. The experimental results show that the proposed method has 100% accuracy in detecting and isolating conventional faults of an LIB system.

4) Other Diagnosis Methods

Reference [221] proposes a battery historical data and internal resistance-based battery fault diagnosis algorithm. Misdiagnose and missed diagnose are avoided because of the combination and comparison of the median absolute deviation algorithm. In [222], active diagnosis is investigated in the framework of discrete event systems, and a necessary and sufficient condition is derived for a system to be actively diagnosable, while controls to achieve the active diagnosis are proposed. Reference [223] proposes a fault identification method based on capacity estimation to estimate and distinguish multi-short circuit and low-capacity cells effectively. These are prone to be misdiagnosed by normal methods. Reference [203] presents a multi-fault diagnosis approach based on a hybrid system. This considers the battery pack as a hybrid system with hierarchical and decentralized diagnostic structure for model complexity reduction and diagnosability improvement. In [34], a multi-fault detecting and isolating scheme is proposed based on the combination of a model-based method and sample entropy. As shown in Fig. 17, the interleaved voltage measurement topology structure is deployed to distinguish voltage sensor faults from connection faults or short-circuit, whereas the residual is then generated using structural analysis and EKF [34]. The residual is evaluated according to the cumulative sum (CUSUM) test to detect and isolate the sensor faults. Finally, the sample entropy method is employed to distinguish connection faults from ISC faults. The proposed algorithm shows good robustness to both noise and inconsistencies.

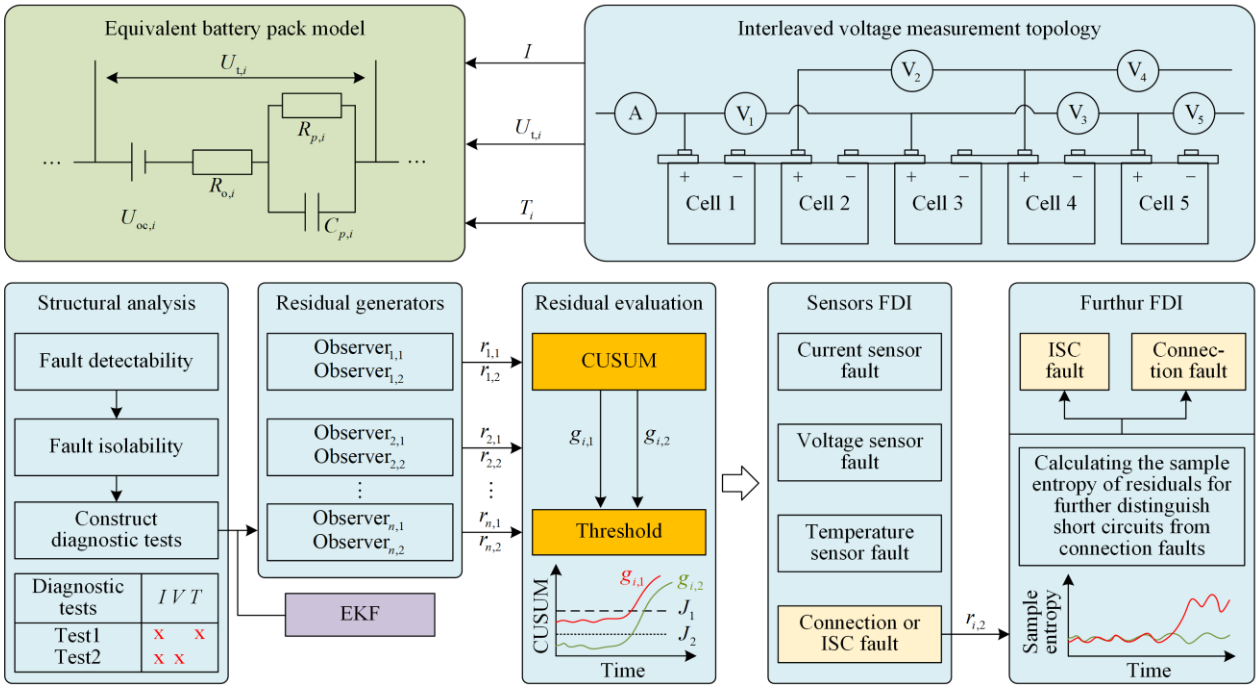

Fig. 17. Diagram of the multifault diagnosis algorithm based on the battery model and sample entropy.

Reference [224] presents the optimal sensor placement strategy for multifault diagnosis in an LIB pack. The structural methodology is employed to illustrate how to select a minimal/optimal sensor set to detect and isolate faults. An FDI scheme case study verifies that the proposed optimal sensor set placement method is able to detect and isolate ISC, ESC, and individual sensor faults in a battery pack. The optimal sensor placement strategy can be applied at the submodule, module, and pack level, so the approach is completely scalable.

V. Current Challenges and Outlook

A. Existing Challenges

Although extensive research has been conducted on fault diagnosis for LIBSs with significant achievements, there are still issues and challenges that need to be addressed as follows.

1) The effect of measurement errors on fault diagnosis has not received serious attention. In practical applications, the process of battery state estimation and fault diagnosis depends on the measured values from the sensors. Voltage sensors often have offset and random errors. The former shows different values on different sensors, which result in battery inconsistency at the data level, whereas the latter is more obvious under conditions of high voltage and current, which reduces the reliability of fault feature extraction results. The introduction of a large time-constant filter in voltage measurement can eliminate the influence of random error, but it will reduce the real-time performance of fault diagnosis and change the performance characteristics of fault features. The method of comparing the amount of state mutation in adjacent time will be seriously affected.

2) Distinguishing battery fault types is difficult. The data sources of a fault diagnosis method include many voltage and current sensors, which detect the external characteristics of changes inside the battery. However, the differences between the external characteristics of different fault types are not obvious, which make it difficult to distinguish them. Also, after a long period of operation, there is often not only one kind of fault existing. This increases the difficulty in distinguishing fault types. In addition, most battery fault diagnosis methods aim to identify and compare the characteristics of specific faults, where the result of feature matching is the diagnosis result. Therefore, when the battery fault characteristics are not accurately extracted, or an unknown type of fault occurs, the fault type cannot be determined.

3) The determination of fault threshold is not theoretical. In many types of fault diagnosis methods, threshold comparison is the last step. However, the determination of threshold values primarily depends on experience while lacking sound theoretical support. A loose threshold will reduce the sensitivity of the algorithm, whereas a strict one will increase the false positive rate of the algorithm. While fault feature extraction can obviously diagnose the fault state, how to set a threshold to reliably eliminate the effects of interference and maintain strong sensitivity is still very challenging and requires systematic work. At the same time, battery aging modifies multiple battery model parameters.

Therefore, in model-based and data-based fault diagnosis methods, model parameters, data feature extraction parameters, detection thresholds, etc., should be automatically updated with the aging of the battery.

4) Battery micro fault detection and early fault warning are difficult. In practical application, the change of data characteristics caused by minor faults is likely to be submerged in the sensor measurement errors and complex working condition data. The identification of minor faults depends on repeated feature matching and validation of long-run data, as well as a large number of micro faults and fault-free operational data at the early stage. Big data-based multi-device and long-term data mining processes can help detect minor faults. However, in practical application, the establishment of data centers only plays the role of remote monitoring, and there is a lack of effective targeted data mining algorithms.

5) The difference between the laboratory and real environment creates a lot of uncertainty. The fault diagnosis methods established in the laboratory usually only consider battery cells or small battery modules, but the actual ESS is a huge and complex system often containing thousands of batteries. In addition, battery voltage and temperature can be measured to high accuracy and high frequency by special instruments in the laboratory. This is very convenient for the estimation of battery status but, in actual ESS, the accuracy of measurement and state estimation is lower. Thus, different data accuracy levels and system structures put forward high requirements for the application of fault diagnosis methods.

B. Outlook

The research outlook for fault diagnosis for LIBSs mainly includes the following four aspects.

1) New Substitute Experiment and High-fidelity Models for Fault Diagnosis

The current fault substitute experimental methods cannot fully simulate the real battery fault processes or characteristics. Thus, it is very important to develop controllable and repeatable fault substitute simulation methods and high-fidelity models with good electrical and thermal fault characteristics to simulate battery faults, especially ISC faults which pose the greatest potential threat to the LIBS. New substitute experimental and high-fidelity models will help to further understand the mechanisms of the fault generation and development process.

2) New Advanced Sensors for Fault Diagnosis

As sensing technology develops, it will be very attractive to use advanced sensors to directly measure the physical and chemical properties inside the battery. Based on various external and built-in advanced sensors, various signals during the battery cycle, such as stress, strain, heat, etc., can be obtained at the same time and feed into the fault diagnosis method to achieve accurate early identification and prediction of faults. For instance, reference [225] employs embedded optical fiber sensors to monitor the internal temperature of a battery, while reference [52] uses vibration sensors to collect vibration signals of LIB packs and proposes a diagnosis method for connection faults in LIB packs based on the vibration signals. In future research, advanced and intelligent sensing technology will become one of the hot spots for producing safer LIBS.

3) Big Data Technology for Fault Diagnosis

Adopting big data technology for fault diagnosis will achieve accurate, robust, and fast fault diagnosis. The application and development of big data technology have made it possible to store and process massive historical battery data. Based on this, machine learning, data mining, and other artificial intelligence techniques can be combined with fault mechanisms to achieve accurate fault diagnosis for LIBS. Based on big data technology, developing cloud-edge collaborative systems can achieve a new safety system for monitoring the health status and diagnosis of faults in LIBSs throughout their entire lifespan.

4) Fault-tolerant Control

The purpose of fault-tolerant control is to reduce the damage of faults in an LIBS and maintain the normal operation of the system when faults occur. The current research on battery fault diagnosis mainly focuses on FDI, while there is less research on fault-tolerant control. After the faults have been detected and isolated, how to carry out effective fault-tolerant control to ensure continuous safe operation of the system is the key to reduce the harm caused by the faults. Therefore, fault-tolerant control needs to be further researched from two aspects: control algorithm and LIBS structure. On LIBS structure, reconfigurable LIBSs with switches are promising for fault tolerance operation because they allow the LIBS to be reconfigured when faults occur [119].

VI. Conclusion

Due to the frequent occurrence of fire and explosion accidents in LIBSs, their safety has become a prominent problem, and has attracted a lot of attention. Advanced and efficient fault diagnosis for LIBSs is essential to troubleshoot issues and ensure safe operation of LIBSs.

This paper presents a comprehensive analysis and detailed summary of the types, characteristics, and diagnosis methods for faults in LIBSs. It illustrates current research progress, existing challenges, and the outlook of fault diagnosis for LIBSs. First, the fault types in LIBSs are summarized, including BMS malfunction, ISC, ESC, TR, and sensor faults, insulation destruction, EC and contactor faults, while their mechanisms and characteristics are elaborated separately. Then, fault diagnosis methods are summarized into four categories, i.e., model-based, data-processing, machine learning-based, and knowledge-based methods. They all have different pros and cons. Next, based on the classified diagnosis methods, current research is comprehensively described. Finally, the existing issues and challenges of fault diagnosis are discussed systematically, and the future development trends are prospected. All this can further boost the development of efficient and advanced fault diagnosis to enhance the reliability and safety of LIBSs.

ACKNOWLEDGMENT

Not applicable.

AUTHORS' CONTRIBUTIONS

Hanxiao Liu: writing-original draft, writing-review & editing, visualization, and the construction of the paper framework. Luan Zhang: writing-original draft, writing-review & editing. Liwei Li: supervision and project administration. All authors read and approved the final manuscript.

FUNDING

This work is supported by the State Key Program of National Natural Science Foundation of China (No. 62133007).

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

DECLARATIONS

Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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