Advanced Fault Diagnosis for Lithium-Ion Battery Systems

A Review of Fault Mechanisms, Fault Features, and Diagnosis Procedures

XIAOSONG HU, KAI ZHANG, KAILONG LIU, XIANKE LIN, SATADRU DEY, and SIMONA ONORI

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Lithium (Li)-ion batteries have become the mainstream energy storage solution for many applications, such as electric vehicles (EVs) and smart grids. However, various faults in a Li-ion battery system (LIBS) can potentially cause performance degradation and severe safety issues. Developing advanced fault diagnosis technologies is becoming increasingly critical for the safe operation of LIBS. This article provides a comprehensive review of the mechanisms, features, and diagnosis of various faults in LIBSs, including internal battery faults, sensor faults, and actuator faults. Future trends in the development of fault diagnosis technologies for a safer battery system are presented and discussed.

Lithium-ion batteries have become the mainstream energy storage solution for many applications.

Fault Modes and Effects

As one of the most promising energy storage systems, Li-ion batteries have been widely used in various applications, such as EVs and smart grids. Li-ion batteries have become the mainstream energy storage solution, owing to their inherent benefits, including a high energy density, high power density, and long life span. However, potential risks due to abusive operating conditions and harsh environments pose a huge challenge to the safety of LIBSs. A real-time, effective battery management system (BMS) is critical to ensure the safety of LIBSs. A BMS has several functionalities, such as state-of-charge (SOC) monitoring, thermal management, charging management, and equalization management. It also tracks the health status and monitors the potential faults of a LIBS. Without suitable diagnostics and fault handling, a minor fault could eventually lead to severe damage of a LIBS [1]. The importance of fault diagnostics and fault handling has been repeatedly demonstrated in several severe incidents [2]–[4].

There are different fault modes in a LIBS, and fault mechanisms are usually very complex. From a control perspective, these fault modes can be divided into battery faults, sensor faults, and actuator faults. Battery faults, which include overcharging, overdischarging, overheating, external short circuits (ESCs), internal short circuits (ISCs), electrolyte leakage, swelling, accelerated degradation, and thermal runaway (TR), are the most critical ones in a LIBS. These faults are also intertwined. Overcharging and overdischarging could lead to various undesirable battery side reactions, resulting in accelerated degradation. The side reactions and gases generated by chain reactions during TR may eventually cause battery swelling. Such swelling, along with mechanical damage, may, in turn, lead to electrolyte leakage.

An ISC is typically caused by a separator failure due to manufacturing defects, overheating, mechanical collisions, and penetration by metal dendrites or mechanical punctures. Fortunately, the Joule heat generated by an ISC develops into TR only when the equivalent ISC resistance reaches a very low level [5]. Abnormal heat generation occurs under various conditions, such as side reactions during overcharging/overdischarging, ISCs, ESCs, and the contact loss of the cell connector, which further increases the battery temperature. Temperature plays an important role in thermal management, battery pack equalization, capacity/power degradation, and TR [6]. Overheating is the direct cause of battery TR and can also be facilitated by chain reactions during TR [7], resulting in a vicious positive feedback cycle.

Feng et al. [8] studied the mechanisms of chain reactions during TR for a Li-ion battery with $(Ni_xCo_yMn_z)O_2$ (NCM)/graphite electrodes and a polyethylene-based ceramic coated separator. The solid electrolyte interface (SEI) decomposition, the reaction between the electrolyte and the anode, the melting of the separator, the decomposition of the NCM cathode, and the decomposition of the electrolyte have occurred sequentially during the process of temperature rise.

In [9], the authors found that 12% of the heat released during the TR of a single cell is sufficient to trigger the TR of adjacent battery cells. Lamb et al. [10] investigated the failure propagation in a multicell Li-ion battery pack when TR is induced in a single cell. They analyzed the failure propagation under different cell types and electrical connections (parallel and series). Feng et al. [11] summarized four approaches to delaying or preventing TR propagation, including increasing the TR onset temperature, improving heat dissipation, reducing the accumulated energy during TR, and adding thermal-resistant layers between adjacent batteries. Hofmann et al. [12] proposed an explosion prevention method by reducing the battery pressure during TR, which is particularly practical for explosions caused by the electrolyte.

Besides battery faults, sensor faults can cause severe issues for LIBS operation because all the feedback-based algorithms in the BMS highly depend on sensor measurements [13]. Sensor faults in a LIBS mainly include voltage sensor faults, current sensor faults, and temperature sensor faults. A current sensor fault affects the accuracy of the SOC estimation [14] and multistate estimation [15], [16]. Estimated SOC and temperature measurements are used to update the battery model parameters in real time for high-accuracy prediction [17], [18]. Li-ion batteries must be operated within safe voltage and temperature ranges [19]. Exceeding these ranges may reduce the battery performance and even cause accidents. Voltage and temperature sensor faults could also cause equalization errors and thermal management errors in the BMS.

Actuator faults have a more direct impact on control system performance than do battery faults and sensor faults. Potential actuator faults in a LIBS, including terminal connector faults, cooling system faults, controller area network bus faults, high-voltage contactor faults, and fuse faults, are summarized in [20]. If the cooling system fails, the battery cannot be maintained within the proper operating temperature range, and it may even trigger TR. A battery connection fault will not only cause insufficient power supply but also increase the risk of accidents [21], [22]. A poor connection between batteries leads to a rise in resistance, and it generates excessive, abnormal heat, which further causes temperature rises [23]–[25]. As the charging and discharging process continues, there may be an arc or spark, resulting in the melting of the battery terminals [26].

A lot of research on fault diagnostics for different components of LIBSs has been conducted. Among the different proposed approaches, the most widely used battery fault diagnosis strategy is the model-based method instead of the data-driven technique because obtaining rich battery fault data is usually time-consuming and costly. In the data-driven approaches, signal processing methods are mainly used for battery fault diagnosis, rather than machine learning-based methods. Sensor faults and actuator faults usually affect the external signals of the battery, such as the voltage, current, and temperature. Therefore, phenomenological models, such as the equivalent circuit model (ECM), are enough for the diagnostic requirements. The ECM is simpler in its computation and structure than electrochemical models (EMs). As a result, it is easier to design various control and diagnostic tools based on the ECM [27]. In general, observer-based methods and signal processing techniques are widely used for sensor fault diagnosis and actuator fault diagnosis, respectively.

However, the fault diagnostics for LIBSs still faces many challenges. These issues will be thoroughly discussed in the "Issues and Challenges" section. To the best of our knowledge, there is no review of fault diagnostics for LIBSs in the existing literature. For a clear and systematic understanding of the state of the art of LIBS fault diagnostics, this article provides a comprehensive review of fault mechanisms, fault features, and fault diagnosis techniques for the Li-ion batteries, sensors, and actuators in a LIBS. The state-of-the-art approaches for LIBS diagnostics and their advantages and limitations are also summarized. In addition, some representative algorithms are classified and discussed to stimulate innovative ideas for LIBS fault diagnosis. Finally, this article discusses future trends and suggestions on improving LIBS fault diagnostics for a safer battery system. For a better understanding of the abbreviations used in this review, a list of all acronyms and abbreviations is shown in Table 1.

Fault Diagnosis Systems

Fault diagnosis is a multidisciplinary technology that involves applied mathematics, control theory, information theory, and reliability theory. To have a better understanding of LIBS fault diagnostics, this section introduces the methodologies of fault diagnosis systems. The basic principles of several representative fault feature extraction and diagnostic algorithms are introduced in detail. Their advantages and disadvantages will also be discussed. In the "Fault Diagnosis for LIBS" section, specific fault features and their applications in LIBS fault diagnosis will be elaborated.

Overview of the Fault Diagnosis System

The terminology used in the fault diagnosis system is shown in Table 2. A flowchart of a general fault diagnosis system is presented in Figure 1. First, data acquisition is used to process and store information from experimental measurements and high-fidelity simulation models, mainly including the voltage, current, and temperature for battery systems. The processed data will be used for model identification, fault characterization, and algorithm

TABLE 1 – ACRONYMS AND ABBREVIATIONS.

ABBREVIATIONS			
3σ MSS	3σ multilevel screening strategy	NCM	$Li(Ni_xCo_yMn_z)O_2$
AEKF	Adaptive extended Kalman filter	NSMC–EVs	National Service and Management Center of EVs
ANN	Artificial neural network		
BMS	Battery management system	OCV	Open-circuit voltage
CCVC	Charging cell voltage curve	PCBG	Parallel-connected battery group
ECM	Equivalent circuit model	PDE	Partial differential equation
EKF	Extended Kalman filter	PF	Particle filter
EM	Electrochemical model	PHM	Prognostics and health management
ESC	External short circuit	PIO	Proportional-integral observer
EV	Electric vehicle	RCC	Remaining charging capacity
FDI	Fault detection and isolation	RF	Random forest
FTC	Fault-tolerant control	RLS	Recursive least squares
ICA	Incremental capacity analysis	SEI	Solid electrolyte interface
ISC	Internal short circuit	SOC	State of charge
KF	Kalman filter	SOH	State of health
LIBS	Lithium-ion battery system	SVM	Support vector machine
MSC	Micro-short circuit	TR	Thermal runaway
MDM	Mean-difference model		

TABLE 2 – THE DEFINITIONS OF THE TERMINOLOGY USED IN FAULT DIAGNOSIS.

TERM	DEFINITION
Fault	An anomaly due to which a system is unable to perform a specified function
Fault mode	The macroscopic behavior of a fault, also known as the type of fault
Fault cause	The key factors causing a fault
Fault mechanism	The nature of changes in physical processes that eventually develop into a fault
Fault feature	The feature or parameter that reflects the abnormality caused by a fault
Fault detection	The process of determining whether a fault has occurred
Fault isolation	The process of determining the type and/or location of a fault
Fault identification or estimation	The process of determining the magnitude/intensity of a fault
Fault diagnosis	The process of detecting, isolating, and estimating a fault

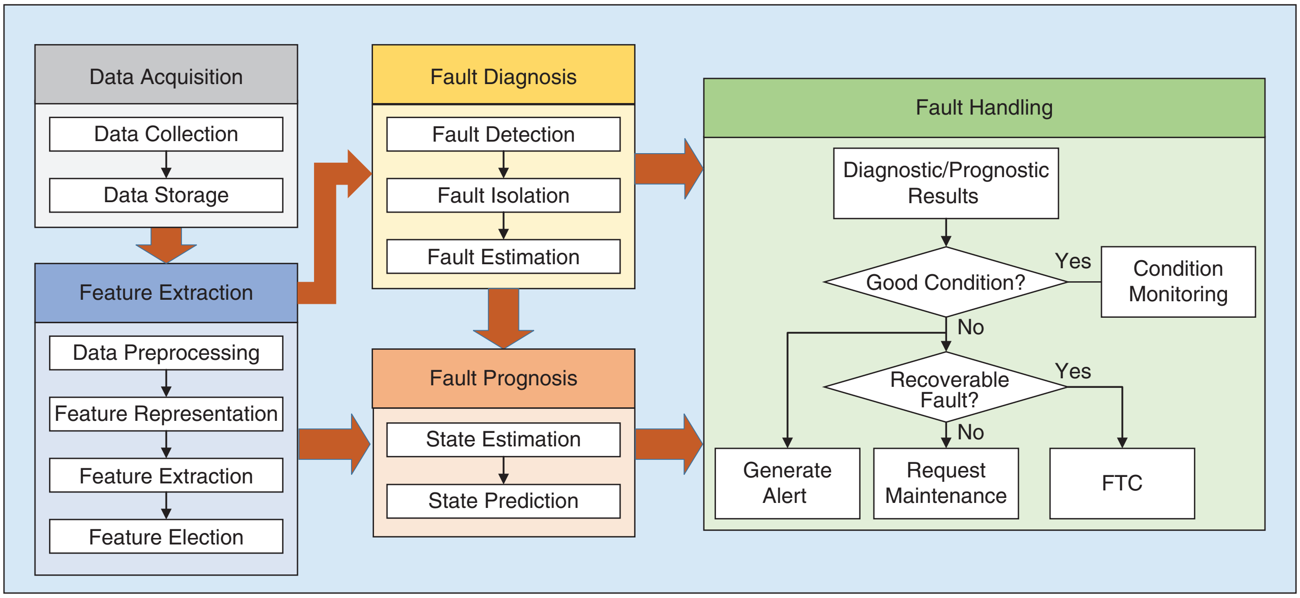

FIGURE 1 – The general fault diagnosis system. Adapted from [29] and [30]. FTC: fault-tolerant control.

TABLE 3 – A COMPARISON OF TWO FEATURE EXTRACTION METHODS.

FEATURE EXTRACTION METHOD	KEY TECHNOLOGIES	ADVANTAGES	DISADVANTAGES
Signal processing-based method	Analyze the measured data directly to determine the fault	No need for system modeling Easy to analyze qualitatively Various applications	Difficult to detect minor and unforeseen faults and to achieve fault isolation
Model-based method	Use state estimation or parameter estimation algorithms to identify changes in the system state and model parameters	Easy to implement quantitative analysis and fault isolation	Affected by model accuracy

verification. Then, key electrical and thermal features are extracted by data preprocessing, feature representation, feature extraction, and feature selection. Subsequently, the fault diagnosis and the fault prognosis can be performed based on the feature extracted.

The tasks of LIBS fault diagnosis can be divided into fault detection, fault isolation, and fault estimation [28]. Their definitions and differences are found in Table 2. Fault prognostics can be used to provide early detection and prediction for some battery faults that have a slow evolution process. Finally, the fault-handling module analyzes and evaluates the results from the fault diagnosis and the fault prognosis and makes decisions, such as alarming, initiating fault-tolerant control (FTC), isolating faulty batteries, and even cutting off the power supply.

Feature Extraction

Feature extraction is a preprocessing step for fault diagnostics. The accuracy of feature extraction highly depends on the method used. Here, we focus on two main feature extraction methods: signal processing-based and model-based. Various signal processing techniques have been developed to extract useful features in the time, frequency, and time–frequency domains, such as the root-mean-square amplitude, spectral analysis [31], wavelet transformation [32], the entropy-based method [33], the rough set [34], and principal component analysis [35]. For example, battery and connection faults can cause abnormal fluctuations in the battery voltage response and temperature response. The entropy-based method [33] can be used to capture these anomalies because of its capability of measuring the degree of randomness or disorder of time series data. Note that some methods, such as the rough set [35] and principal component analysis [35], can reduce the dimension of the fault features, which is very useful for reducing the complexity of the diagnostic system.

Based on the measurements, model-based state estimation and parameter estimation methods can be used to extract fault features. In battery systems, fault features can be characterized by changes in battery states and model parameters. For example, a connection fault can cause a significant change in the battery contact resistance. ISC faults and thermal faults can be characterized by the SOC decrease and ohmic internal resistance increase, respectively. For different fault models, a filter [17], observer [18] or least-squares algorithm [36] needs to be designed accordingly to extract key states or parameters. Theoretically, artificial intelligence algorithms can also be applied to extract fault features as an alternative to the physics-based model. This method is expected to extract more accurate features with online training and continuous improvement but with the computational cost of continuous training.

For battery system faults, the advantages and disadvantages of the previous two types of feature extraction methods are shown in Table 3.

Many battery system faults can cause capacity losses, extra charge depletion, increased heat generation, and increased battery cell inconsistency. This abnormal behavior can be captured by analyzing the external voltage and temperature response of the battery system by using signal processing methods. The signal processing method does not require modeling work, but it may not achieve fault isolation, as some of the battery faults have similar electrical and thermal responses. Besides, the signal processing method can only detect faults when the abnormality in the battery system response reaches a certain level, which makes it difficult to detect minor issues. In contrast, it is easier for the model-based method to quantify and locate specific faults by exploiting the relationship between faults and model states or parameters.

Diagnostic Methods

There are many studies of diagnostic methods. As shown in Figure 2, we classify the diagnostic methods into the knowledge-based, model-based, and data-driven ones, according to [19] and [37]–[40].

Knowledge-Based Methods

These diagnostic methods utilize the knowledge and observation of battery systems and are especially suitable for nonlinear and complicated systems, such as LIBSs, without the need for developing mathematical models. Although their working principles and diagnostic results are easy to interpret, further studies on LIBS fault mechanisms, knowledge acquisition, and knowledge representation are still required when they are applied to LIBS fault diagnosis. The most widely used knowledge-based

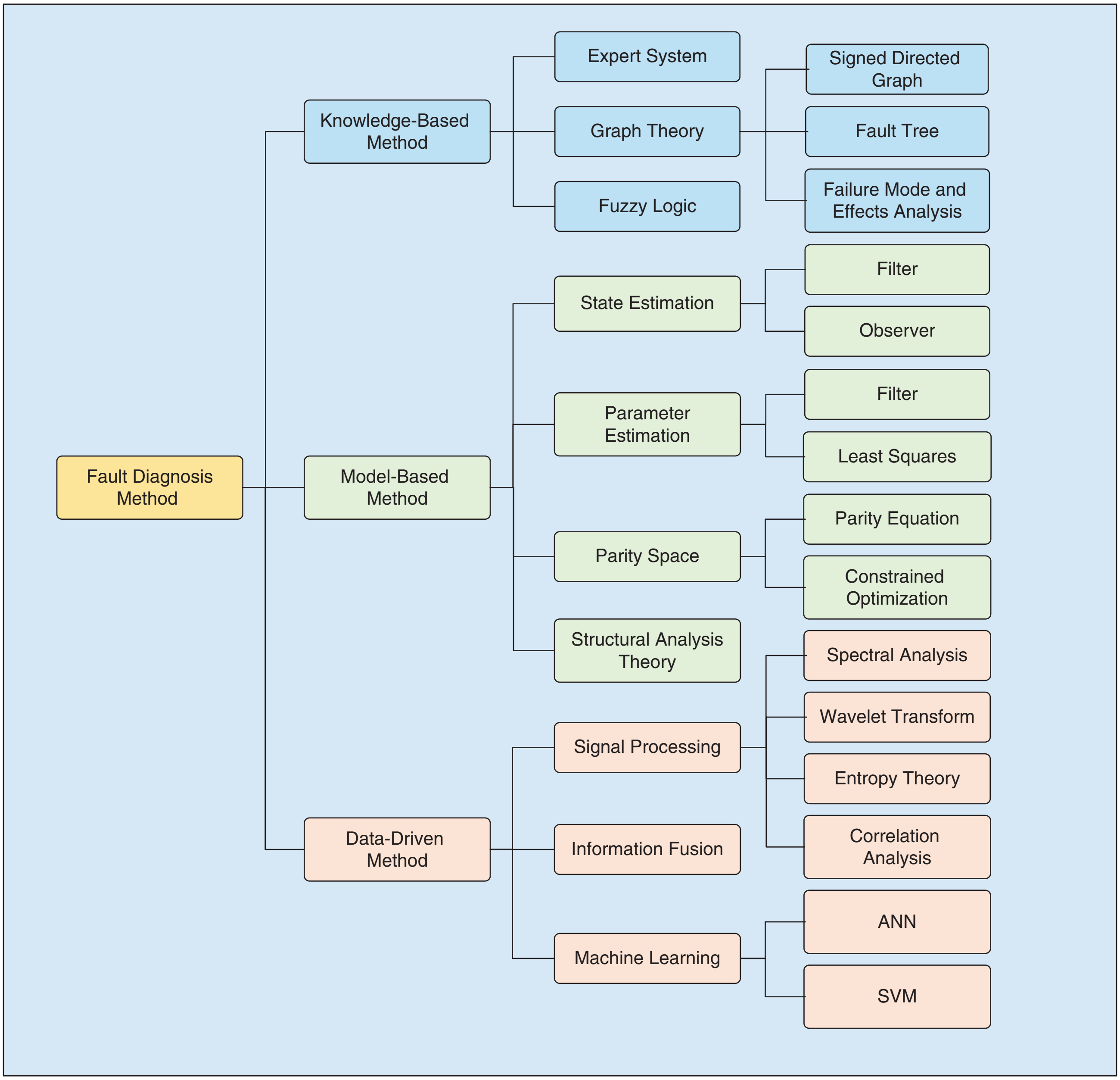

FIGURE 2 – The classification of fault diagnostic methods. ANN: artificial neural network; SVM: support vector machine.

methods include those based on graph theory and fuzzy logic as well as the expert system.

Specifically, by using graph theory, such as a signed directed graph [41], fault tree [42], and failure mode and effects analysis [43], a fault diagnosis network can be constructed based on the fault propagation relationship between various components in the system. Then, a fault can be located using the relevant search theory. An expert system is a computer program designed to simulate the reasoning and decision making of human experts [44]. The knowledge and rules are established by utilizing a historical database and the rich experience from domain experts. Fuzzy logic, which conforms to the natural thinking process of human beings and facilitates the processing of qualitative knowledge, can be applied to fault diagnosis by using fuzzy parameters, fuzzy models, and fuzzy thresholds.

Table 4 gives a comparison of various knowledge-based diagnostic methods in terms of their key technologies, advantages, and disadvantages. Multiple battery faults, sensor faults, and actuator faults may occur in the battery system. Graph theory has a clear causal relationship, and its diagnostic results are easy to interpret. However, the complex fault mechanisms of the battery system make it difficult to establish an accurate diagnostic network. The expert system method does not require a physics-based model. However, there also exist several problems when it is applied to battery systems, such as difficulties in knowledge acquisition and inaccurate knowledge representation. The fault states of batteries can be characterized by anomalies such as a rapid SOC decline, intense heat generation, and large voltage fluctuations. These fuzzy parameters can be processed by the fuzzy logic method. However, developing effective rules is still a big challenge.

Model-Based Methods

For model-based fault diagnostics, a residual signal is typically obtained by comparing the measurable signal with the signal generated by the model [45]. Subsequently, the residual will be evaluated to determine the diagnostic results [46]. The development of high-fidelity battery models [47], including electrical models, thermal models, and multiphysics models, provides the basis for model-based fault diagnosis. Thanks to their in-depth understanding of battery system dynamics, these methods can not only detect faults but also locate faults and estimate their magnitude. Therefore, they are becoming the mainstream method for LIBS fault diagnostics. It should be noted that these methods could be affected by model uncertainty, interference, and noise. Model-based methods can be divided into four categories, including the state estimation, parameter estimation, parity space, and structural analysis theory.

State estimation methods essentially utilize an observer or filter to reconstruct or estimate the internal states, such as the SOC and the internal temperature of batteries. After that, the residuals containing the fault information can be obtained by comparing the estimated signals with the sensor measurements [37]. The basic idea of the parameter estimation for fault diagnosis is that faults will affect the physical system process, further leading to changes in model parameters [48], [49]. Therefore, the fault detection and isolation (FDI) of a LIBS can be achieved by spotting changes in the battery's electrical model and thermal model parameters. The dynamic model of the battery system determines the relationship between the input and output variables. The parity space method can be used to verify this relationship by analyzing the input and output measurements of the battery system [50], [51]. Structural analysis theory finds and utilizes the structural overdetermined part of system dynamic equations [52] and then achieves the structural detectability and isolability analysis of faults [53]–[58].

A comparison of the preceding model-based methods is given in Table 5. Various filters and observers have been applied to fault diagnosis for LIBSs, such as the Kalman filter (KF) [59], extended KF (EKF) [60], unscented KF [61], particle filter (PF) [62], Lunberger observer [63], and adaptive observer [64]. The state estimation method can help the state-monitoring function of the BMS and detect the fault with excellent real-time performance.

In comparison, parameter estimation methods, such as filter techniques [65] and least-squares approaches [66], can be combined with other methods to locate specific LIBS faults. However, they require a higher battery model accuracy and sufficient current excitations [67]. For the parity space methods, such as the parity equation approach

TABLE 4 – A COMPARISON OF KNOWLEDGE-BASED DIAGNOSTIC METHODS.

KNOWLEDGE-BASED METHOD	KEY TECHNOLOGIES	ADVANTAGES	DISADVANTAGES
Graph theory	Diagnostic network Fault propagation relationship Search strategy	Clear causality Easy to interpret the diagnosis results Easy to analyze qualitatively	Needs a thorough understanding of the fault mechanism Not suitable for systems with high complexity
Expert system	Knowledge acquisition and representation Knowledge base Rule base	No need for a mathematical model Diagnostic results are easy to understand.	Difficulty in knowledge acquisition and representation Overreliance on the representativeness and integrity of knowledge
Fuzzy logic	Fuzzy rules Membership function	Suitable for handling qualitative knowledge and reasoning	No self-learning ability Difficult to develop effective rules

[68] and the constrained optimization technique [69], the fault isolation of sensors and actuators in LIBS can be easily achieved based on the different hypothesized no-faulty-subsets of inputs and outputs. One obvious advantage of structural analysis theory is the ability to provide fault detectability and isolability analysis regardless of the LIBS parameter values, which greatly reduces the workload of designing residual generation for fault isolation.

Data-Driven Methods

These methods directly analyze and process the running data to detect faults without relying on the accurate analytical model and the experience of experts. For the data-driven fault diagnosis of a LIBS, the fault detection process is simplified by not considering the complicated fault mechanism and system structure, especially for TR and the accelerated degradation of a battery, which are affected by various unclear and coupled factors. However, the implementation of this method generally requires a proper preprocessing of raw data for LIBSs. Due to the neglect of fault mechanisms, it is not easy to analyze and interpret faults using this method. Furthermore, some data-driven methods also present inherent limitations, such as the need for a large amount of historical data, accompanied by a high computational cost and training complexity [70]. The data-driven methods commonly used in fault diagnosis domain include signal processing, machine learning, and information fusion.

Fault diagnosis based on signal processing usually uses various signal processing techniques to extract fault feature parameters, such as deviation, variance, entropy, and the correlation coefficient. After that, the fault will be detected by comparing parameters with the values during a normal state. ANNs [71] and SVMs [72] are two typical machine learning algorithms. ANN-based fault diagnosis learns the implicit rules from a given pair of inputs and outputs during an offline training phase and then forms a nonlinear black-box model for use during the online operation phase. A well-trained ANN can distinguish between the normal and abnormal states of a battery system.

The main function of SVM-based fault diagnosis is to transform the input space into a high-dimensional space through a kernel function and to find the optimal hyperplane in this new space. This method treats LIBS fault diagnosis as a sample classification problem and trains an accurate classifier based on historical data. Information fusion represents a process of reasoning and decision making based on uncertain information. Based on the analysis of multisource information, more reliable fault detections can be achieved.

Table 6 presents a comparative analysis of these data-driven diagnostic methods. Due to its neglect of LIBS dynamics, the signal processing method is easy to implement and suitable for fault detection, but it is difficult to directly locate faults in the case of multiple LIBS fault coupling. Machine learning algorithms have the ability to adapt the training sample set by adjusting its parameters, and they have the ability to extract knowledge from current training samples. Theoretically, the battery black-box model based on the ANN can achieve a higher accuracy than the EM and the ECM of a battery. However, the lack of LIBS fault data may cause overfitting problems. That is, ANNs with a poor generalization ability are likely to cause an undesired false alarm of the LIBS fault.

Compared with ANNs, SVM has a better generalization ability and is

TABLE 5 – A COMPARISON OF MODEL-BASED DIAGNOSTIC METHODS.

MODEL-BASED METHOD	KEY TECHNOLOGIES	ADVANTAGES	DISADVANTAGES
State estimation	Reconstruct system state with filters or observers	Good real-time performance No need for a large number of inputs stimulus	Difficult to determine the fault location and damage degree
Parameter estimation	Estimate system parameter or fault parameter	Conducive to fault isolation	Requires high-precision modeling and sufficient input excitations
Parity space	Equivalent relationship between input and output variables expressed by the system model	Simple, fast Suitable for fault isolation	Affected by model accuracy and noise
Structural analysis theory	Structural analysis of system dynamic equations	Easy to analyze fault detectability and isolability Workload of selecting residual generators is reduced	Strongly dependent on the redundant information of the system model

TABLE 6 – A COMPARISON OF DATA-DRIVEN DIAGNOSTIC METHODS.

DATA-DRIVEN METHODS	KEY TECHNOLOGIES	ADVANTAGES	DISADVANTAGES
Signal processing	Appropriate signal processing techniques	Easy to implement Applicable to both linear and nonlinear systems	Difficult to detect minor faults and directly locate faults Not suitable for systems with highly coupled components
Artificial neural network	Neural network structure Dynamic adjustment of variable weights	Self-learning from samples Strong adaptability Parallel processing	Need massive historical data and long training time Poor generalization ability Overfitting problems
Support vector machine	Kernel function selection	Good generalization ability Applicable to small sample cases	Difficult to select the optimal kernel function Low efficiency for large-scale training sets
Information fusion	Appropriate information fusion algorithms	More accurate diagnostic result	Difficult to select effective fusion algorithms

applicable to small sample cases [73], which is especially suitable for a LIBS with a limited amount of fault data. The most critical issue related to SVMs is the optimal kernel function selection for a specific problem. To make full use of existing multisource information concerning a LIBS to improve the accuracy of the fault diagnosis, an effective fusion algorithm is essential.

FTC

FTC is used to maintain safe operation and meet certain performance requirements when a fault occurs in a system [74]. An FTC architecture is shown in Figure 3. In general, FTC can be classified into active and passive types [75]. There are few existing studies on FTC in LIBSs, and passive FTC is used in most cases.

The purpose of passive FTC is to design a strong controller such that the system is robust against certain faults [76]. Passive FTC assumes a prior knowledge of faults, and therefore, does not need to know the real-time fault information or adjust the controller online. However, passive FTC may be ineffective against unknown faults. Hu et al. [77] developed a dual-redundancy method to achieve FTC of temperature sensors. When a sensor fault occurred, the optimal value determined by relevant algorithms was taken as the sensor output value to ensure the proper operation of the system. Berdichevsky et al. [78] demonstrated that each cell was equipped with two fuses for the cell's anode and cathode in the Tesla Roadster battery pack. This scheme mainly relies on the structural design of the battery system, and it can effectively prevent the entire battery system from malfunctioning in the case of a short circuit. However, the requirement of substantial additional components would make the battery structure complicated.

In contrast, based on real-time information about a fault, active FTC will readjust the controller parameters and even change the configuration after the fault occurs. That is, active FTC can process a fault in real time so that the system can still achieve its specified functions under fault conditions [79]. Despite a high complexity and large computational cost, this method greatly improves the system performance, which has attracted increasing attention in both academia and industry. Therefore, the application of active FTC in LIBSs has the potential to become an important research field.

Evaluation System

For battery system faults, the performance of the diagnostic system will vary based on different methods. A good evaluation system can compare various diagnostic algorithms and help design a better fault diagnosis method. The key to establishing a good evaluation system for fault diagnosis is to establish a reasonable performance index system and develop appropriate evaluation methods [81].

According to different functionalities, the major performance indexes for the diagnostic system can be roughly divided into detection performance, diagnostic performance, and robustness [82], [83]. Detection performance can be assessed by sensitivity, time delays, false alarm rates, missed detection rates, and misclassification rates. This index is closely related to the timeliness of fault handling for LIBSs. Diagnostic performance refers to the capability of fault isolation and the accuracy of the fault estimation. False alarms and missed detections are common indices of LIBSs, and they can cause additional troubleshooting and safety risks. Robustness is the most difficult performance index to measure and achieve. A diagnostic algorithm without the robustness to model uncertainty, interference, and noise can hardly be used in practical LIBSs.

To date, there are no standardized evaluation methods for LIBS fault diagnosis. In general, a diagnostic system evaluation method follows the

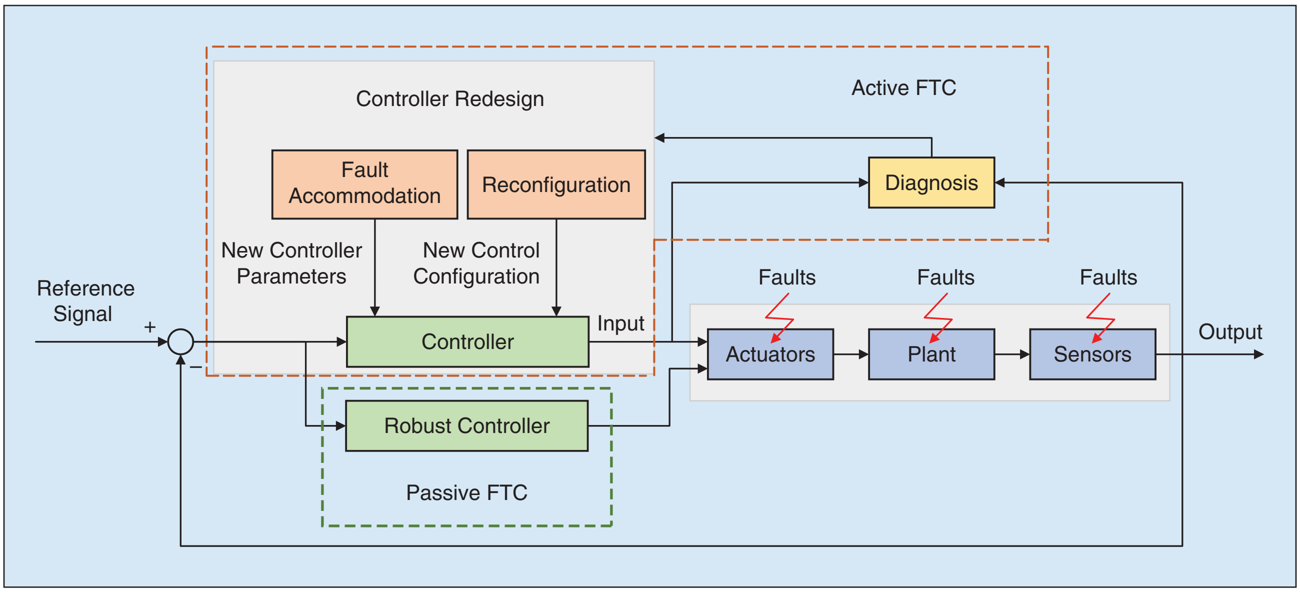

FIGURE 3 – The architecture of FTC. Adapted from [80].

process of determining the weight of each index, evaluating each index, and determining the final evaluation result. The weight has a big impact on the final evaluation results. Typically, the weight is related to the importance and reliability of indexes. For example, a battery short circuit fault has a higher weight than a sensor fault, owing to its greater threat to a LIBS. In most cases, it is difficult to evaluate some indicators quantitatively, for example, robustness. One possible solution is to first qualitatively evaluate each index and then quantify the qualitative index in a unified framework.

Fault Diagnosis for LIBSs

Fault diagnosis is critical to ensure the safety of LIBSs. Therefore, it is necessary to study the fault mechanisms, fault features, and diagnostic methods for LIBSs. Figure 4 illustrates the faults in LIBSs. Faults in LIBSs are affected by inherent defects, improper use, and harsh environments. Therefore, these internal and external factors and their complicated coupling relationship make fault diagnosis of LIBSs a difficult task. In general, LIBS faults are hidden, and it is difficult to directly and accurately determine early fault conditions by using voltage, current, and temperature signals only. Each type of fault poses a certain threat to a LIBS. Battery faults could lead to system performance degradation and even catastrophic accidents, such as battery fires and explosions. BMS sensor faults will affect the normal operation of the control system, leading to ineffective state estimation, equalization management, and thermal management in a LIBS. Actuator faults often lead to ineffective control actions, a situation that further affects the system response.

Li-Ion Battery Fault Diagnosis

Li-Ion Battery Fault Mechanisms

Studies of battery fault mechanisms provide useful insights into the battery failure process. The understanding of fault mechanisms serves as a foundation for developing the fault diagnostic methods. Currently, a few review papers have been published about the fault mechanisms of Li-ion

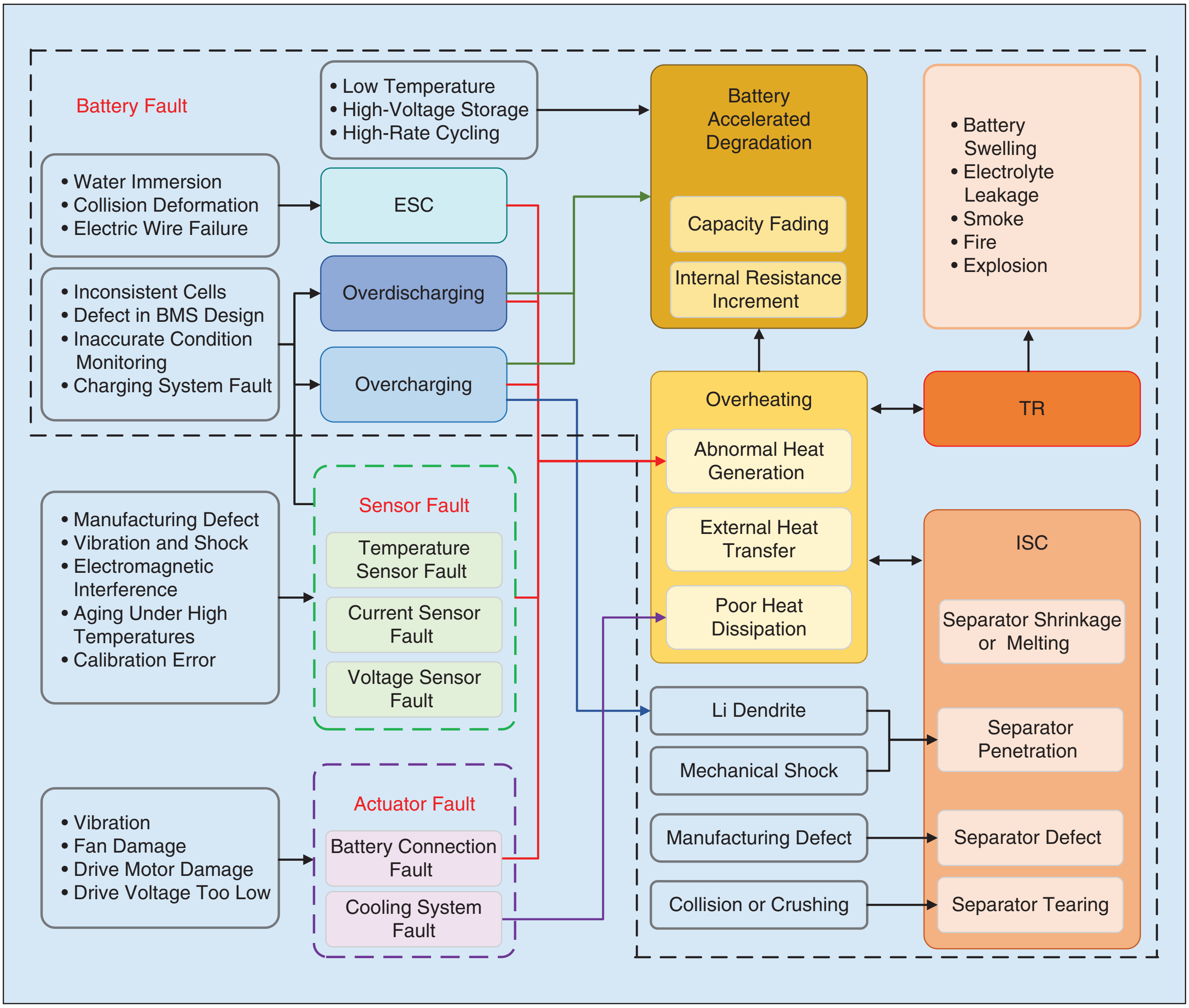

FIGURE 4 – The faults in Li-ion battery systems.

batteries [84]–[87]. At the microscopic level, Alavi et al. [27] summarized several electrochemical failures, such as the loss of electrical contact, current collector corrosion, SEI growth, electrolyte decomposition, fractures in the lattice structure of electrodes, Li plating, the loss of active material, negative electrode diffusion coefficient reduction, porosity changes of the electrode, and changes to the particle size. In addition, several battery faults, including overcharging/overdischarging, accelerated degradation, swelling, electrolyte leakage, ESCs, ISCs, overheating, and TR, are very important in real applications.

Although the cutoff voltage can be preset in the protection circuit, overcharging and overdischarging faults still occur in EVs due to inconsistencies among cells, inaccurate condition monitoring, and charging system faults [88]. For example, if the voltages of series cells are not monitored well in the BMS, the cells that have the highest and lowest voltages will be overcharged and overdischarged, respectively, resulting in the rapid aging of the battery. Accelerated battery degradation is caused by undesired side reactions within a cell, which are accompanied by the losses of cyclable Li ions and active material [89], [90]. Typically, these adverse side reactions, such as the phase change and decomposition of the cathode material [91], electrolyte decomposition [89], SEI decomposition, and growths at the anode [92], [93], are caused by various external factors [38], including overcharging/overdischarging, a low temperature, a high voltage storage, and high-rate cycling. Specifically, the excessive delithiation of the anode causes SEI decomposition during overdischarging [94]. After recharging, the newly regenerated SEI changes the electrochemical properties of the anode [95], resulting in an increase of the resistance and the degradation of the capacity [96].

Repeated overdischarging will accelerate battery capacity degradation, the extent of which depends on the depth of the discharge [88]. During overcharging, Li deposition (the mossy or dendritic type) will occur at the surface of the anode [97]. Meanwhile, the overdeintercalation of Li will contribute to an irreversible phase change and even the collapse of the cathode structure, with a gas release and heat generation.

Temperature is also a very important factor affecting battery operation. Under low-temperature charging conditions, Li plating is more likely to occur at the anode due to the slow diffusion process [98]. High temperatures can cause SEI decomposition and accelerate the capacity fade. The battery capacity can drop significantly when it is operated or stored at temperatures higher than 50 °C, especially in the high SOC range [6]. Under high-rate discharge conditions, a large amount of Li-ion is transferred in a short time, which may cause an incomplete deintercalation of the Li ions and a capacity loss.

Battery swelling, electrolyte leakage, and ESC faults are often caused by other battery or component faults. There exists a causal relationship between them. First, the gas generated by the side reactions during overcharging and the chain reactions during TR may cause the internal pressure to rise, and there may even be an explosion. Then, battery swelling and mechanical damage become the main causes of electrolyte leakage. Finally, electrolyte leakage can further cause a battery ESC as well as the short circuiting of adjacent electronic components. Besides, EVs may suffer from water immersion, collision deformation, and electric wire failure during operation. Therefore, an ESC may also occur when electrodes with voltage differences are accidentally connected by conductors [99]. An ESC is a fast discharge process and results in abnormally high heat generation.

An ISC, one of the most common faults in TR, can be caused by different separator failures, such as deformation, penetration, shrinkage, and melting. For example, mechanical loading [100] can cause the deformation and fracture of the separator, and the electrical short circuit under mechanical loading is generally predicated by the formation of internal cracks in the battery stack [101]. Separator penetration can be caused by mechanical shock and dendrites due to overcharging and overdischarging [62]. Moreover, the TR reaction is more severe when a penetration occurs at the center of a battery [102]. The separator shrinkage or melting caused by high temperatures and the contamination of the separator by impurities are also the causes of separator failure [103]. Once a separator fails, an ISC is triggered by the contact between the anode and the cathode. The battery capacity [104] and the heat accumulated during the initial phase [105] are key factors in determining the consequences of ISCs. Studies [106] show that the worst location for an ISC is the edge of the electrode, where the heat dissipation is limited by the low thermal conductivity of the electrolyte and separator materials.

Overheating and TR have mutually reinforcing relationships. The causes of TR are summarized in [99], including mechanical, electrical, and thermal abuse. Specifically, thermal abuse or overheating is the direct cause of TR. Overheating is usually caused by abnormal heat generation, external heat transfer, and poor heat dissipation. Abnormal heat generation occurs in many scenarios, such as side reactions during overcharging and overdischarging, ESCs, ISCs, and battery connection faults. A portion of the heat could be transferred to adjacent cells and the environment. Moreover, faults and the improper design of the cooling system can also result in poor heat dissipation. Battery overheating caused by these factors may trigger TR; the mechanism of chain reactions during TR for a Li-ion battery is elaborated in [107], including capacity degradation at the high temperature, SEI decomposition, the reaction between the anode and the electrolyte, separator melting, cathode decomposition, electrolyte decomposition, the reaction between the anode and the binder, electrolyte burning, and so forth.

Li-Ion Battery Fault Features

It is important to note that, unlike sensor and actuator faults, data acquisition is a key step in battery fault diagnosis. Therefore, the state of the art of data acquisition for battery fault diagnosis is discussed in this section before the Li-ion battery fault feature. Besides the real-time data from EVs, data acquisition can also be achieved through substitute tests and simulation models in academic research.

Many test methods have been developed for Li-ion battery research, such as penetration [106], mechanical loading [108], [109], external heating [110], overcharging [111], and ESC tests [112]. The implementation of the aforementioned test methods often requires a combination of advanced techniques, including optical, infrared, chemical, and thermal methods [111], [113]–[115]. For an ISC fault, the most concerning battery fault, the currently accepted ISC substitute tests mainly include penetration, adding phase-change material into the separator, inducing dendrite growth through electrical abuse, and connecting an equivalent ISC resistance in parallel to the cell. Moreover, a new approach to conduct the ISC substitute test is provided by controlling the separator porosity and the pressing force [116]. Because the experimental test methods are costly and time consuming, a lot of research has been devoted to developing a high-fidelity model that can simulate battery failure behavior, such as the ECM [60], [117], two-state thermal model [118], electrochemical–thermal model [119], [120], 3D electrochemical–thermal model [105], 3D electrochemical–thermal-ISC coupled model [66], [121], mechanical–electrical–thermal coupled model [122], and finite element model [123].

In general, the Li-ion battery fault feature can be obtained from two sources. First, the battery fault feature can be directly extracted from measurements or transformed from basic features. Second, the fault feature of a battery can also be reflected by certain model parameters. In general, battery faults are typically difficult to determine through current, voltage, and temperature measurements. Instead, fault features are often extracted from the abnormal responses caused by faults through signal processing. For example, due to the extra charge depletion, an ISC can be inferred by two implicit features, including the continuous reduction of the SOC and the rising heat generation [124]. These two features can be captured by the responses of the battery voltage and temperature [125]. For a short circuit under mechanical abuse conditions, a local force drop [126] can be regarded as a fault feature, which is consistent with the voltage drop and temperature rise.

Moreover, fault features transformed from basic characteristics enable detecting battery faults more sensitively. For example, in [117], the differential of the voltage and the fluctuation function of the internal resistance are considered as the fault features. In [125], the correlation coefficient between cell voltages can capture the abnormal voltage drop. The entropy of the battery temperature [127] and voltage [128] become the features of temperature abnormity and voltage fault, respectively.

For the quantitative analysis of faults, certain parameters of the battery model are regarded as fault features, such as the ISC equivalent resistance [129] and the thermal model parameters [63], [130] related to convective cooling resistance faults, internal thermal resistance faults, and TR faults. Liu [131] and Wu [132] analyzed the relationship between battery faults and parameter changes and summarized the diagnostic rules for common battery faults. In many studies, certain model parameters are regarded as the state of health (SOH) indicator, such as the capacity and the internal resistance [133]–[135]. However, the results derived from these parameters may vary under different operating conditions [136].

Since certain electrochemical properties are uniquely related to the degree of the battery degradation regardless of operating conditions, they can be used as an indicator of the battery SOH, such as the side-reaction current density [137]. It should be noted that most battery fault features are at the cell level. In the case of series-connected battery modules, the difference of the SOC as well as ohmic internal resistance [36], [138] in the mean-difference model (MDM) of the battery pack can be used as effective ISC fault features.

Li-Ion Battery Fault Diagnosis Methods

Due to a lack of internal information and the strong coupling among various battery faults, many conventional diagnostic methods applied in other fields are not suitable for battery fault diagnosis. Currently, methods used in battery fault diagnosis mainly consist of model-based, data-driven, knowledge-based approaches as well as methods of integrating multiple techniques. A comparison of battery fault diagnosis methods appears in Table 7.

Based on the battery model and measured data, model-based methods use the state estimation and parameter estimation techniques to generate residuals and detect faults. Fault isolation can be achieved by constructing a fault signature table. Due to its simplicity and intuitive nature, the model-based method is widely used for fault diagnosis in battery cells and packs [139]. Based on the EM, Alavi et al. [62] estimated the transport rate of Li ions in both positive and negative electrodes by the PF algorithm and then compared the estimated data with the boundary condition to detect the Li plating. Because overcharging and overdischarging can cause the model parameters to change, Sidhu et al. [59], [60] constructed multiple battery signature fault models through impedance spectroscopy technology and an equivalent circuit methodology, using a KF or an EKF to estimate the model terminal voltage and generate residuals. A probability-based approach was also applied to indicate the likelihood of failure. But this method is accompanied by the difficulty of identifying multiple models and running an EKF.

Dey et al. [63] added convective cooling resistance, internal thermal resistance, and TR faults into a two-state thermal model; the FDI is designed for these three thermal faults based on the Luenberger observer. In [30], Dey et al. extended their previous work to consider the temperature dependence of internal resistance and incorporate a Lyapunov-based nonlinear observer approach to deal with the nonlinearities of a battery. Moreover, in [140], they utilized a partial differential equation (PDE) model-based scheme and realized the detection and estimation of the size of the thermal fault.

Since the excessive charge depletion and abnormal heat generation of the ISC cells affect the voltage and temperature responses, the correlation can also be captured by the phenomenological model. Feng et al. [66] estimated model parameters using recursive least squares (RLS) with a forgetting factor. Their model includes parallel resistance, capacitance, ohmic resistance, and the temperature derivative of the equilibrium

TABLE 7 – A COMPARISON OF BATTERY FAULT DIAGNOSIS METHODS.

DIAGNOSTIC METHOD	REFERENCES	BATTERY FAULTS	FAULT FEATURES	ADVANTAGES	DISADVANTAGES	PRACTICAL LIMITATIONS
RLS	[36], [66], [117], [138], [141]	MSC, ISC, capacity-fade fault	Ohmic resistance, capacitance, SOC difference, differential of the voltage	High precision Low computational cost	Affected by model uncertainty and SOC estimation accuracy	Needs information regarding other cells in series Affected by cell inconsistency and balancing
PF	[62]	Li plating	Transport rate of Li ions	Insensitive to noise	Affected by model uncertainty	High computational cost
EKF	[59], [60]	Overcharging, overdischarging	Battery model parameters	Insensitive to noise	Complexity of multiple models	High computational cost
Luenberger observer	[63]	Thermal faults	Thermal model parameters corresponding to different thermal faults	Quantitative assessment of faults	Sensitive to noise	Poor robustness against measurement noise
Nonlinear observer-based on Lyapunov analysis	[130]	Thermal faults	Thermal model parameters	FDI for three thermal faults	Affected by model uncertainty	Needs high model accuracy
PDE-based observer	[140]	Thermal faults	Thermal model parameters	High precision	Complicated PDE model	High computational cost
ICA	[133]–[135]	Capacity loss	*dQ/dU*, capacity	More sensitive than traditional charge–discharge curves	Sensitive to measurement noise	Affected by battery inconsistency, cycling rate, and temperature
Correlation coefficient	[125], [142]	Short circuit fault, voltage fault	Abnormal voltage drop, correlation coefficient	Insensitive to cell inconsistencies Hardware or analytical redundancy not required	Sensitive to measurement noise	Affected by cell balancing
CCVC transformation	[143]	MSC	RCC	Low computational complexity	Subject to SOC estimation accuracy	Difficult to work in real time Affected by cell balancing
Entropy method	[127], [128], [144]	Temperature and voltage fault within battery packs	Entropy of battery temperature and voltage	Applicable to a wide range, especially abnormal fluctuations of a chaotic system	Computation window has significant effects on the results of entropy	High computational cost
RF	[145]	Electrolyte leakage of ESC cells	Discharge capacity and maximum temperature increase	Good classification ability Low computational cost	Needs a large amount of training data	A large amount of fault data is not easily available
ANN	[146]	Battery fault	Abnormal voltage	Accurate Insensitive to the model uncertainty	A large amount of training data is required	A large amount of fault data is not easily available
Rule-based method	[149]	Overcharging	Increase of temperature and decrease of voltage	Easy to implement and understand	Not easy to determine the appropriate parameters in the rules	Poor robustness against unknown interference
Fuzzy logic	[150]	Overcharging, overdischarging, and aged battery	Parameters derived from voltage, temperature, and SOC	Easy to deal with uncertainty in knowledge	Poor self-learning capability	High computational cost
Fusion method of integrating expert knowledge, machine learning, and machine vision	[151]	Battery separator defects	Optical effects unrelated to quality	High precision Good robustness	High system complexity	High computational cost

potential in the energy conservation equation. Then, the ISC fault detection was implemented based on the changes in these key parameters. Seo et al. [129] proposed a model-based switching method to detect ISCs. By introducing the ISC resistance to the battery model, the accuracy of the open-circuit voltage (OCV) estimation is improved, and the ISC resistance can be estimated more accurately.

Another implementation of the model-based method is to combine the information concerning adjacent cells in a battery pack. The fault diagnosis can be achieved based on the difference among the battery states and model parameters between a faulty cell and a normal one. For example, Feng et al. [138] proposed a model-based ISC fault diagnostic scheme, as shown in Figure 5. They first calculated the voltages and temperatures of both the average and the worst cells, and the worst cells have the highest likelihood of an ISC fault. Then, the cells' SOCs and internal ohmic resistances were obtained based on the state estimation and parameter estimation methods, namely the EKF and the RLS with a forgetting factor. Finally, the ISC fault and its fault level were determined by the deviations of the voltage, temperature, SOC, and internal ohmic resistance between batteries.

Zhang et al. [141] estimated the resistance of the parallel-connected battery group (PCBG) and identified the capacity fade fault by comparing the PCBG resistance among different PCBGs. Moreover, two fault causes, an inconsistent aging fault and a loose contact fault, can be distinguished by comparing the PCBG resistances. Ouyang et al. [117] estimated the basic parameters of the MDM by the RLS algorithm and then calculated the differential of the voltage and the fluctuation function of the internal resistance. Based on a statistical method, the ISC fault is determined by comparing the estimated and calculated parameters with the threshold. Given that the micro-short circuit (MSC) causes the SOC difference to increase continuously, Gao et al. [36] estimated the SOC difference based on the MDM with an EKF. The extra depleting current is identified, and the short circuit resistance is detected and calculated. Without the need for estimating the SOC of each cell, this method can quantitatively describe an ISC fault with a small computational cost.

The signal processing method is a typical data-driven technique that directly extracts useful fault features from battery measurement data to detect faults. It does not require the construction of an accurate battery analytical model and is suitable for a wide range of applications. Dubarry et al. [133]–[135] applied incremental capacity analysis (ICA) to identify various contributions to capacity loss; ICA is more sensitive than traditional charge–discharge curves. The correlation coefficient can be used to determine whether the trends of two voltage curves match with each other. For example, Xia et al. [125] proposed a short circuit fault diagnosis scheme by using this method, as shown in Figure 6. The voltage of each cell in the battery pack is readily available, but battery inconsistency makes it difficult to determine battery faults directly from the voltage. Therefore, Xia et al. captured the abnormal voltage drop by calculating the correlation coefficient between cell voltages. Then, the short circuit fault was detected by comparing the calculated correlation coefficient with the threshold.

According to the mathematical properties of the correlation coefficient algorithm, this method is robust against the inconsistencies in the OCV and internal resistance, and the detection process does not require hardware or analytical redundancy. Using the real-time voltage data extracted from the National Service and Management Center of Electric Vehicles (NSMC–EV) in Beijing, Li et al. [142] verified the voltage fault detection of a battery pack based on the interclass correlation coefficient method. Considering that the remaining charging capacity (RCC) of the MSC cell will increase when a battery pack is fully charged each time due to the extra charge depletion, Kong et al. [143] estimated the RCC of each cell based on the uniform charging cell voltage curve (CCVC) hypothesis. According to the difference between the RCCs after two adjacent charges, the leakage current and the MSC resistance can be obtained. Based upon a large amount of raw temperature data derived from the NSMC–EV, Hong et al. [127] applied Shannon entropy to capture the temperature abnormity of the battery pack. Besides, the abnormity coefficient, including the overtemperature and excessive temperature difference, was quantitatively evaluated to predict both the time and the location of the temperature faults in battery packs.

Wang et al. [128] employed modified Shannon entropy to analyze the voltage evolution of each cell and accurately predict both the time and the location of a voltage fault in battery packs. Liu et al. [144] regarded all cell voltage values at each time step as an index and implemented the entropy weight method to obtain the objective weight of each index. According to the comprehensive score and the threshold, battery voltage abnormality can be accurately identified.

Another typical data-driven method is machine learning, which acquires the underlying laws from a large number of battery-training samples. However, it is currently less used in battery fault diagnosis due to the difficulty in obtaining large amounts of battery fault data. For example, Yang et al. [145] proposed a method based on the random forest (RF) classifier to detect the electrolyte leakage of ESC cells, as illustrated in Figure 7. The leaked cells have a lower discharge capacity and a higher maximum temperature rise. Therefore, these two features were fed into the pretrained RF model. First, every training subset S_i was resampled randomly from the training data set using the Bootstrap method, and then every single decision tree C_i was generated by the corresponding S_i. Finally, the output classification results indicate the leakage conditions, which are determined by the voting results of all the decision trees. With a large number of offline ESC fault tests, the trained RF classifier can rapidly get the correct result.

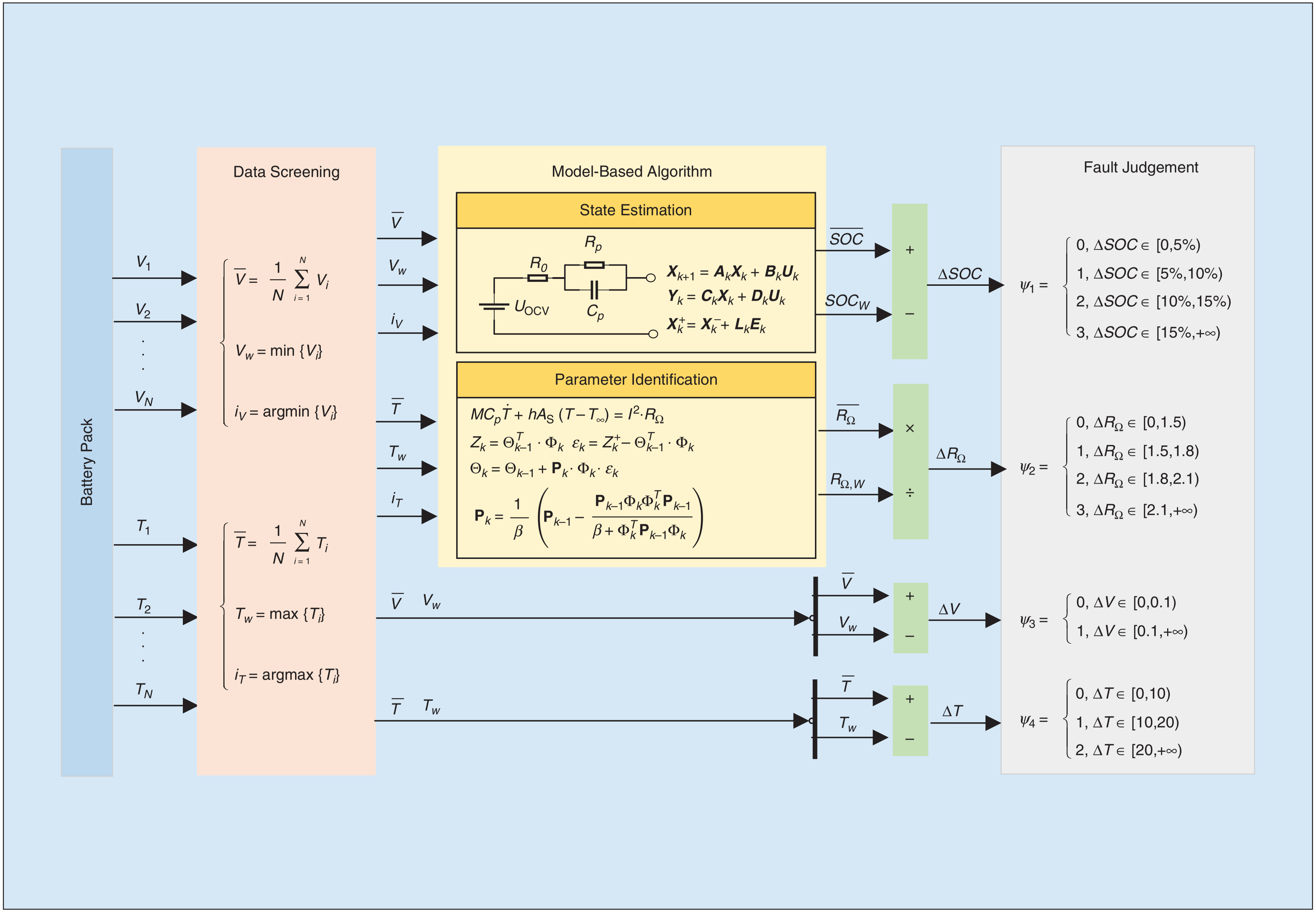

FIGURE 5 – The model-based fault diagnosis for ISC detection. Reproduced with permission from [138] (©2018 by Elsevier).

Zhao et al. [146] combined the 3σ multilevel screening strategy (MSS) and machine learning algorithm to establish a battery fault diagnosis model, in which the 3σ MSS is utilized to build the criteria of fault-free cell terminal voltages, and a neural network is applied to fit the cell fault distribution in a battery pack. Kim et al. [147], [148] proposed a distance-based outlier detection approach with a Z-score standardized preprocessing method for battery fault diagnosis. The estimated capacity and resistance parameters were subjected to cluster analysis for detecting the healthy cells, shorted cells, and aged faulty cells.

Knowledge-based fault diagnosis relies on the understanding of battery mechanisms and long-term accumulated knowledge and experience. Xiong et al. [149] proposed a rule-based detection method for overdischarged Li-ion batteries. Based on the increase of the temperature and the decrease of the voltage during a battery overdischarge, temperature and voltage rules are established, respectively, and the failure detection and early warning are directly given by a Boolean expression. However, the appropriate fixed or time-varying thresholds in the rules are not easy to determine in real applications.

Muddappa et al. [150] designed an EM-based observer to generate voltage, temperature, and SOC residuals. Then, these residuals, along with the temperature change rate, voltage level, and SOC level, were all incorporated into the fuzzy rule to detect various fault types, including overcharging, overdischarging, and battery aging. Huber et al. [151] proposed a method for the classification of battery separator defects using optical inspection

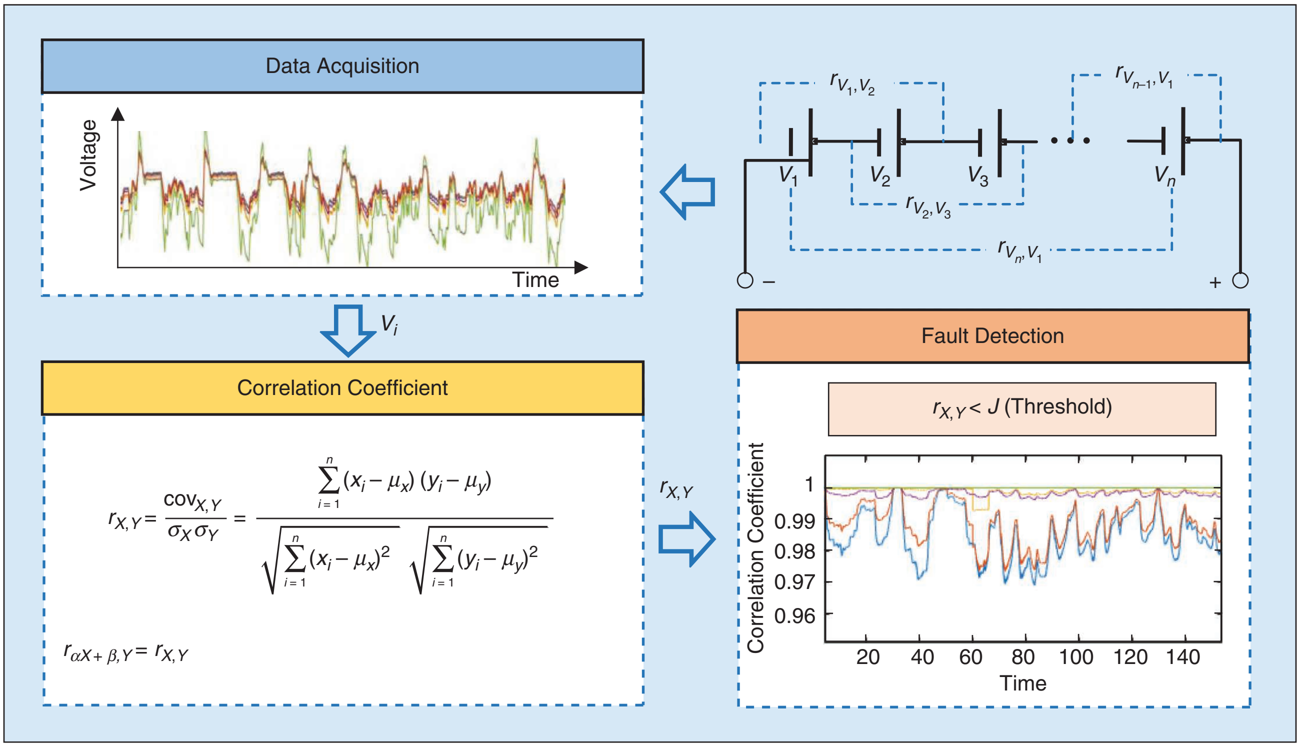

FIGURE 6 – A short circuit fault diagnosis scheme based on the correlation coefficient method. Adapted from [125] and [142].

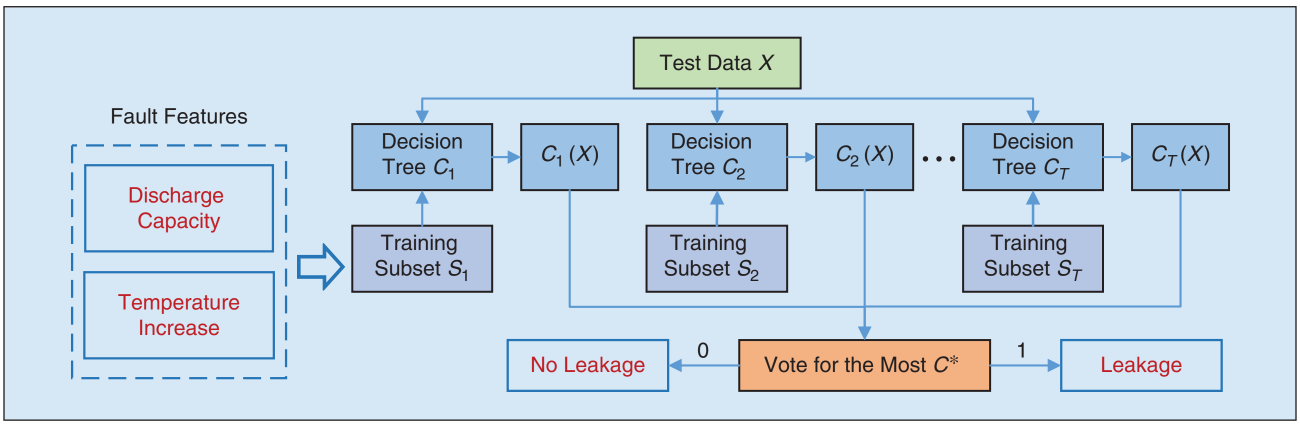

FIGURE 7 – Electrolyte leakage fault detection based on the RF classifier. Reproduced with permission from [145] (©2018 by Elsevier).

and combined various techniques, such as expert knowledge, machine learning, and machine vision, in the diagnosis process. This method of integrating multiple diagnostic techniques generally has a high precision and robustness but at the cost of significant computational complexity.

Sensor Fault Diagnosis

Sensor Fault Mechanisms

In general, the reliability of sensors is affected by manufacturing defects and harsh environments and working conditions. The sensors in the LIBS discussed in this article mainly monitor the voltage, current, and temperature. Conventional current and voltage sensors used in EV battery systems are Hall effect sensors. Additionally, some advanced technologies, such as constant current source circuit acquisition and isolation amplifier acquisition, are also applied in the monomer voltage acquisition. Thermocouples and resistance temperature detectors are commonly used temperature sensors. For Hall effect sensors, temperature variations can change the magnetic properties of the ferrite core, and there could be some flaws developed in the core, such as corrosion, cracks, and breakage, all of which could result in the bias [152]. Due to mechanical shocks and other causes that can change the value of the Hall voltage, changes in the orientation of the induced magnetic field would lead to a scaling error. For thermocouples, the failure of a thermocouple junction, such as corrosion, degradation, and changes in the material composition at long-term high temperatures, can lead to bias, scaling, and intermittent and/or complete failure [153]. For resistance temperature detectors, exposure to high temperatures through time as well as vibrations and shocks can change the characteristics of the detector further leading to signal drift [152], [154].

Sensor Fault Features

Since sensor faults affect measurement signals directly, the fault features of voltage, current, and temperature sensors are often considered as some form of a bias, drift, scaling, or complete failure signal in sensor measurements [19], [155]. Additionally, sensor faults can also be classified into additive and multiplicative faults [37], [45]. In [155], typical ranges for common sensor faults from the literature are summarized, which provides realistic magnitudes to the sensor faults. The voltage measurement is one of the most critical metrics in a battery system due to its high sensitivity to common electrical faults, including short circuits, overcharging, and overdischarging [156].

Sensor Fault Diagnosis Methods

Table 8 describes the sensor fault diagnosis methods used in a battery system; they can be divided into three types: sensor topology-based,

TABLE 8 – A COMPARISON OF SENSOR FAULT DIAGNOSIS METHODS.

DIAGNOSTIC METHOD	REFERENCES	ACHIEVEMENTS	ADVANTAGES	DISADVANTAGES	PRACTICAL LIMITATIONS
Fault-tolerant voltage measurement method	[157]–[159]	Fault isolation of sensor or cell	Able to isolate the sensor fault and cell fault	High noise level	Only suitable for series battery packs with interleaved voltage measurements
Kirchhoff's law	[13]	FDI of voltage, current, and temperature sensor	Simple Low computational cost	Subject to noise and model uncertainty	Not suitable for fault estimation
Structural analysis theory	[20], [52], [169]	FDI of voltage, current, and temperature sensor	Convenient detectability and isolability analysis Smaller workload for designing a residual generator	Highly dependent on redundant information from the system	Poor robustness against noise and model uncertainty
PIO	[14]	Fault detection and estimation of current sensor	Accurate Easy to implement	Improper setting of PIO parameters may cause instability	Needs high model accuracy and proper parameters of PIO
Nonlinear parity equation method	[168]	FDI of voltage, current, and temperature sensor	Efficient Easy to detect large faults	Minimum detectable fault magnitude is limited by the observer error	Needs high model accuracy Low sensitivity to fault detection
Sliding-mode observer	[18]	FDI and fault estimation of voltage, current, and temperature sensor	Good noise robustness	Sensitive to model uncertainty	Needs high model accuracy
EKF	[17]	Fault detection of voltage or current sensor	Insensitive to noise and inaccurate initial values	An accurate process noise covariance is not easily determined	Affected by the process noise and model accuracy
AEKF	[170], [171]	FDI of voltage and current sensor	Insensitive to noise and inaccurate initial values Update the noise covariance matrix	High computational cost	Needs high model accuracy
Fusion method integrating EKF and structural analysis theory	[52]	FDI of voltage, current, and temperature sensor	Accurate: low false alarm rate and missed detection rate	High system complexity	High computational cost

model-based, and fusion. The sensor topology-based method mainly relies on the sensor configuration and the redundancy of sensor functionalities, which is easy to implement. Xia et al. [157], [158] proposed a fault-tolerant voltage measurement method for series-connected battery packs by measuring the total voltage of multiple cells instead of measuring the voltage of individual cells. Then, a matrix interpretation of the sensor topology was developed. For this sensor topology, sensor and cell faults can be isolated by locating abnormal signals without an additional hardware expense.

Kang et al. [159] presented a multifault diagnostic scheme that combines the voltage measurement topology and the correlation coefficient method, in which the correlation coefficient is used to detect fault features. In this sensor topology, each cell and connection resistor is associated with two sensors, which enables the isolation of voltage sensor faults, short circuit faults, and connection faults.

The model-based method generates a residual by using sensor measurements and a priori information or constraint relationships expressed by the model. After analyzing and evaluating the residuals, the magnitude, type, and location of faults can be determined. Typical battery models for sensor fault diagnosis include the EM [160]–[162], the ECM [163]–[167], lumped-parameter thermal models [168], [169], and two-state lumped parameter thermal models [52].

Lombardi et al. [13] tested the electrical relationship between the current sensor and voltage sensor measurements based on Kirchhoff's law to generate residuals and achieve the FDI of the voltage and current sensors according to the battery pack structure and the residual set associated with each sensor. Liu et al. [169] proposed a systematic scheme to apply structural analysis theory to detect and isolate the voltage, current, and temperature sensor faults. Specifically, structural overdetermined parts of the system model have been found, and subsequently, fault detectability and isolability analysis have been performed. Then, diagnostic tests are developed by selecting the minimum overdetermined set. Finally, the residuals are generated by checking the analytical redundancy relationship in each test. Structural analysis theory [20], [52], [169] can effectively reduce the workload in selecting residual generators. However, this type of analysis is easily affected by noise and model uncertainty.

Due to the inaccurate initial values, unknown interference, and noise, residuals generated directly through the constraint relationships from a model may carry errors. Observers and filters can reduce the impacts of these factors, and sensor fault diagnosis based on various observers follows a similar process, as shown in Figure 8. These methods first estimate the battery states based on the battery model and current, voltage, and temperature sensor measurements. Then, the residuals containing the sensor fault information are generated by comparing the measured and estimated outputs. Finally, the FDI of the sensor faults can be achieved through residual evaluation, and the alarms and the fault flag should be set. Xu et al. [14] took the current sensor fault as a bias signal to the system input and used the proportional-integral observer (PIO) to implement fault detection and estimation. Although this method is accurate and easy to implement, improper setting of the PIO parameters may cause instability of the diagnostic system.

Marcicki et al. [168] provided a scheme based on a modified nonlinear

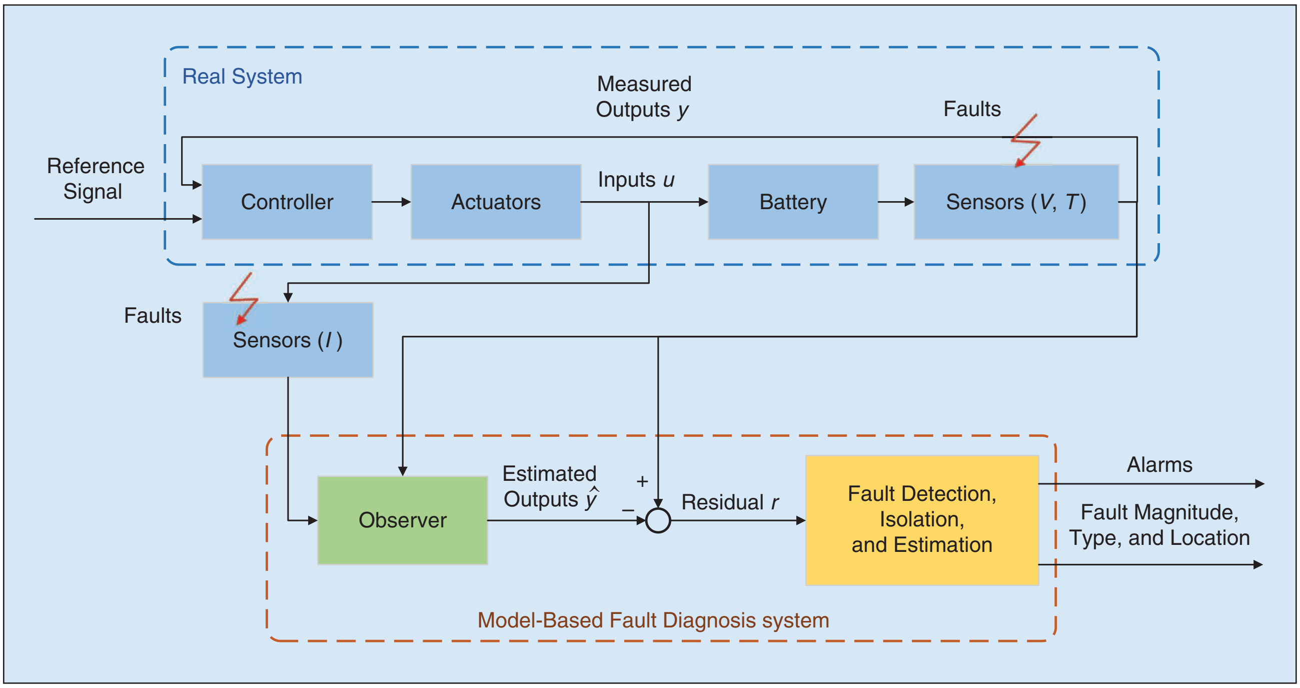

FIGURE 8 – Observer-based sensor fault diagnosis.

parity equation method to achieve voltage, current, and temperature sensor FDI. In the method, a subset of inputs and outputs is hypothesized to be nonfaulty. Under this assumption, the residuals are generated by the forward and inverse models of the system, but the minimum detectable fault magnitude is limited by the observer error. By adding the bounded deviation to the sensor measurement, Dey et al. [18] achieved the fault detection, isolation, and estimation of voltage, current, and temperature sensors by using a sliding-mode observer method. Liu et al. [17] presented a model-based diagnostic scheme using an EKF to estimate the output voltage for detecting current or voltage sensor faults; the approach is robust against inaccurate initial values and noise. However, the accurate process noise covariance matrix in an EKF is not easy to determine in practice. He et al. [170], [171] achieved the FDI of the current and voltage sensors in a series battery pack based on an adaptive extended KF (AEKF), which shows a better noise robustness because an AEKF can adaptively adjust the process and measurement noise covariance matrix.

Strategies combining multiple model-based methods can compensate for the inherent flaws in a single method. For example, Liu et al. [52] constructed two diagnostic tests based on the structural analysis theory. Then, the residuals were generated based on an EKF in each diagnostic test. The generated residuals were further evaluated by the statistical cumulative sum test to detect the sensor faults. This fusion scheme reduces the effort required to find the appropriate residual generator and is robust against noise and inaccurate initial values. But it also increases the system complexity and computational cost.

Actuator Fault Diagnosis

Actuator Fault Mechanisms

Research on actuator fault diagnosis in a battery system mainly focuses on the battery connection fault and the cooling system fault [20], [26]. During EV operations, vibrations may contribute to loosing or poor electrical connections between batteries [26]. Once the operating and driving voltage becomes too low, the relay and drive motor cannot operate as specified. Fan failures are often caused by electric wire faults and blade damage, which, along with motor faults, would severely affect the normal operation of the cooling system.

Actuator Fault Features

Similar to battery fault features, actuator fault features can also be derived from abnormal system behavior and equivalent fault parameters. If a battery connection fault occurs, the resistance will increase dramatically and generate significant heat. Moreover, a single high intercell contact resistance can cause an uneven current flow, resulting in a severe imbalance in a battery pack [172]. Therefore, some features, such as the increased contact resistance, temperature rise, and voltage inconsistency, can be used to characterize the connection fault. In the system model, the battery connection fault can be considered as a gain fault due to the sharp increase in the internal resistance caused by a poor connection. A cooling system fault is often considered as an additive fault because it will cause a deviation of the effective heat transfer coefficient in the thermal model.

Actuator Fault Diagnosis Methods

Actuators with different functionalities have various fault mechanisms and features. There is no universal diagnostic method for actuator fault diagnosis. Two typical diagnostic methods are the model-based and signal processing techniques. The model-based approach can be directly applied to the fault diagnosis of the cooling system. The cooling system, including the cooling fan and the drive motor, is used in a battery system to increase the rate of cooling. The effective heat transfer coefficient, a parameter in the thermal model, varies with the type of convection. Therefore, a cooling system fault could be regarded as a thermal model parameter deviation, which can be detected by typical model-based methods. Liu et al. [20], [169] used the structural analysis theory to implement the cooling system FDI based on the lumped thermal model. Marcicki et al. [168] detected a cooling system fault caused by the failure of the fan motor based on the nonlinear parity equation method.

It is also important to note that the entropy method [173] is an effective tool to describe the degree of disorder of time series; it has a wide range of applications and is suitable for handling actuator faults with abnormal fluctuations, such as battery connection faults. Taheri et al. [174] studied the energy loss caused by the contact resistance of Li-ion battery assemblies for the first time. Zheng et al. [33] proposed an entropy-based connection fault diagnosis scheme, as shown in Figure 9. Their preliminary analysis identified the two reasons for battery pack power fading, including internal and contact resistance increase faults. To account for the internal and contact resistance in the resistance calculation, the voltage is usually measured between the ends of the cell and the connecting wire. Then, the authors established a simplified battery ECM and identified the model parameter containing the contact resistance by the total least-squares algorithm. Considering that poor contact conditions between batteries can make the contact resistance highly unstable, they captured the unstable characteristics of the contact resistance by calculating the Shannon entropy of the cell resistance and realized the distinction between the cell fault and the connection fault.

Yao et al. [26] identified the cell connection state by calculating the entropy value of the cell terminal voltage. After a comparative analysis of sample entropy, local Shannon entropy, and ensemble Shannon entropy, it is found that the ensemble Shannon entropy can predict the accurate time and location of a battery connection failure in real time. Sun et al. [175] used Shannon entropy to process the cell voltage measurements after wavelet transformation and accurately detected the battery connection fault. Compared with the Shannon entropy iteration method used in [26], this method simplifies the calculation process and is easier to implement due to the relatively reasonable interval parameters.

Issues and Challenges

Issues and challenges in LIBS fault diagnosis can be divided into two categories: those related to the diagnostic objects and those related to diagnosis or control. The issues associated with the diagnostic objects are summarized as follows:

1) Many battery fault mechanisms have not been fully understood. For a wide variety of Li-ion batteries, there is no unified understanding of the battery fault mechanisms in the existing literature.
2) Standardized substitute test approaches for battery faults have not been developed. Some destructive methods have poor controllability and repeatability, and they often instantaneously trigger severe faults, which fails to simulate the incubation phase of a fault.
3) There is no well-established mathematical model to accurately describe the behavior of some faults. This applies, for example, to models that simulate the growth process of Li dendrites.
4) The relationships between external behaviors and internal mechanisms are not clear. Different conditions could cause the same fault. However, most of the existing research focuses only on a single fault mechanism, without considering the coupling between different fault processes.

There are also some diagnostic or control-related challenges, such as:

1) The commonly available battery data are voltage, current, and temperature measurements, which do not contain any information about the internal electrochemical dynamics in a battery. Extracting the appropriate features to characterize the internal state of a battery remains a challenge.
2) The internal battery state is difficult to monitor directly due to the uncertainties with modeling and measurement.
3) The fault data in LIBSs are challenging to obtain, which limits the application of data-driven algorithms.
4) The threshold is closely related to fault detection's false alarm rate, missed detection rate, and time delay. The fixed threshold and double threshold do not meet the requirements of complex real-world scenarios, and few studies have been conducted to develop the adaptive threshold.
5) It is not easy to detect some minor battery faults at an early stage. However, such faults could have already caused serious harm to a battery system by the time they are observed. It is also difficult to correct these unrepairable faults through the battery system itself.
6) Most studies on sensor fault diagnosis and battery fault diagnosis are based on the assumption that other components are trouble-free. Isolating a battery fault from a sensor fault is still a challenging issue.
7) One of the challenges in the fault diagnosis of parallel-connected battery packs is that there is no observability and controllability because only one voltage sensor and one current sensor are used. Therefore, for a battery pack that has many parallel-connected cells, only

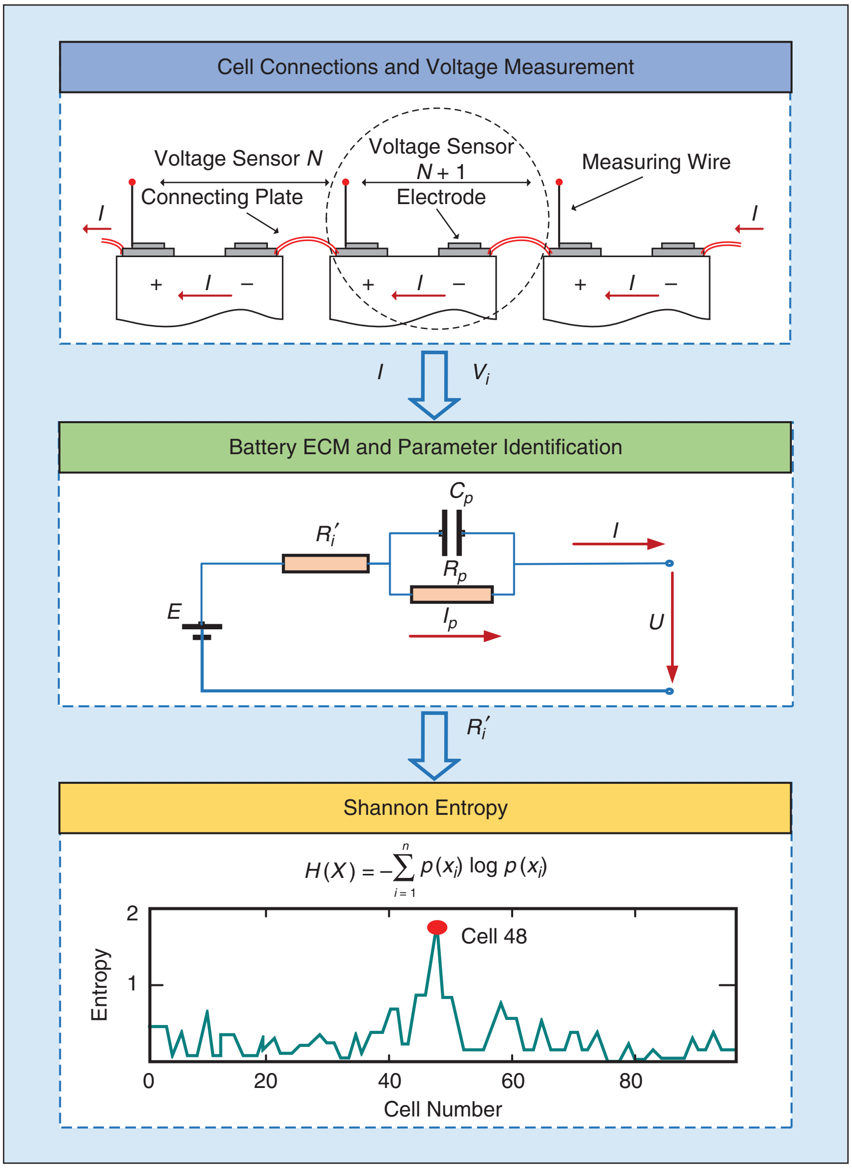

FIGURE 9 – Battery connection fault diagnosis based on the entropy method. Reproduced with permission from [33] (©2013 by Elsevier).

Multiscale mechanism studies from the material, cell, and pack levels help to provide an in-depth understanding of battery system faults.

the battery-pack-level faults can be detected. However, the parallel configuration and the traditional sensor placement make it difficult to accurately locate a particular faulty cell in parallel-connected strings. A better sensor placement design and advanced diagnostic algorithms are needed to solve this problem.

8) The reviewed methods and algorithms provide a wide spectrum of available solutions for the fault diagnosis of battery systems. However, many model-based and data-driven algorithms mentioned in this article cannot currently be applied in practical applications due to the strict requirements of practical applications. The effectiveness of many model-based and data-driven methods is tested only through simulation studies. Experimental studies are needed to verify the approaches' effectiveness. Moreover, the performance of the model-based and data-driven diagnostic algorithms mentioned in this article is affected by many factors in practical applications, including a model's accuracy, interference and measurement noise, algorithm robustness, the quantity and quality of data, battery inconsistency, the sensor topology, and the battery pack configuration. When the algorithms are applied to a certain scenario, they should be properly customized and tuned.

Future Trends in Battery System Fault Diagnostics

Based on the discussion in previous sections, it is clear that the fault diagnosis of battery systems has a multidisciplinary nature. To develop a robust, reliable, effective battery fault diagnosis system, some important tasks need to be completed for different stages of the process, including preparation, analysis, and handling, which are summarized in Figure 10.

Preparation Stage

During the preparation stage, detailed mechanism research, advanced data acquisition, and processing techniques are essential for battery fault diagnosis. Multiscale mechanism studies from the material, cell, and pack levels help to provide an in-depth understanding of battery system faults. The damage caused by faults could be contained by the fault diagnosis and safety protection at all levels. With the increasing demand for the rapid charging of EVs, the battery fault mechanism under fast-charging conditions should be further investigated. Various side reactions promoted by high-rate charging could contribute to accelerated degradation and TR. Moreover, it is also important to develop controllable and repeatable fault substitute tests as well as high-fidelity models for simulating real faults, especially for the ISCs that present the greatest potential threat to battery system safety.

To improve the diagnostic performance throughout the entire life span of the battery, the effects of battery aging on diagnostic performance should also be considered. It is important to update and correct the model parameters of a battery, such as the capacity and internal resistance, by using advanced techniques, including the model-based, machine learning, and fusion methods. Note that a battery ages slowly through time; therefore, the model parameters need to be updated across a long timescale or offline.

Data acquisition using intelligent sensors and integrated chips is also expected, owing to the sensors and chips' high accuracy and versatile functionalities. As the sensing technologies evolve, it will be very attractive to use advanced sensors to measure the physical and chemical characteristics within a battery directly. For example, based on built-in piezoelectric sensors [176], an electrochemical acoustic time-of-flight analysis can be done to capture the implicit correlation between waveform signal parameters and between a battery's SOC and SOH. Omega load cell sensors [177] have been applied to measure the cell expansion caused by the swelling of the electrode's active material during charging. In addition to regular measurements, including the voltage, current, and temperature, fiber optic sensors [178] are capable of monitoring additional cell parameters, (e.g., strain), and they are also robust against electromagnetic interference. In future research, fast and accurate sensing technologies will continue to be one of the hot topics for a safer battery system.

Feature extraction at the battery pack level is an important task. A number of studies on the fault diagnostics of LIBSs have been conducted by using the voltage response of battery cells and series-connected battery packs [125], [128], [138], [157]. However, there are few studies on the voltage response of parallel-connected battery packs [141]. It is worth noting that due to the self-balancing mechanism of the parallel structure, a battery fault can also cause transient voltage fluctuations in adjacent, parallel cells within the same module.

In the existing literature, the widely used features of thermal-related faults are the temperature rise and fluctuation caused by abnormal heat generation. In fact, thermal-related faults can also affect adjacent cells and lead to an uneven temperature distribution in a battery pack. Therefore, useful fault features can be derived by exploring the temperature distribution in a battery pack. In addition, suitable fault features can also be developed through feature transformation and the fusion of multiple electrical and thermal characteristics.

Analysis Stage

During the analysis stage, the accurate examination of the battery system state, including the condition monitoring, fault diagnosis, and fault prognosis, plays an important role in

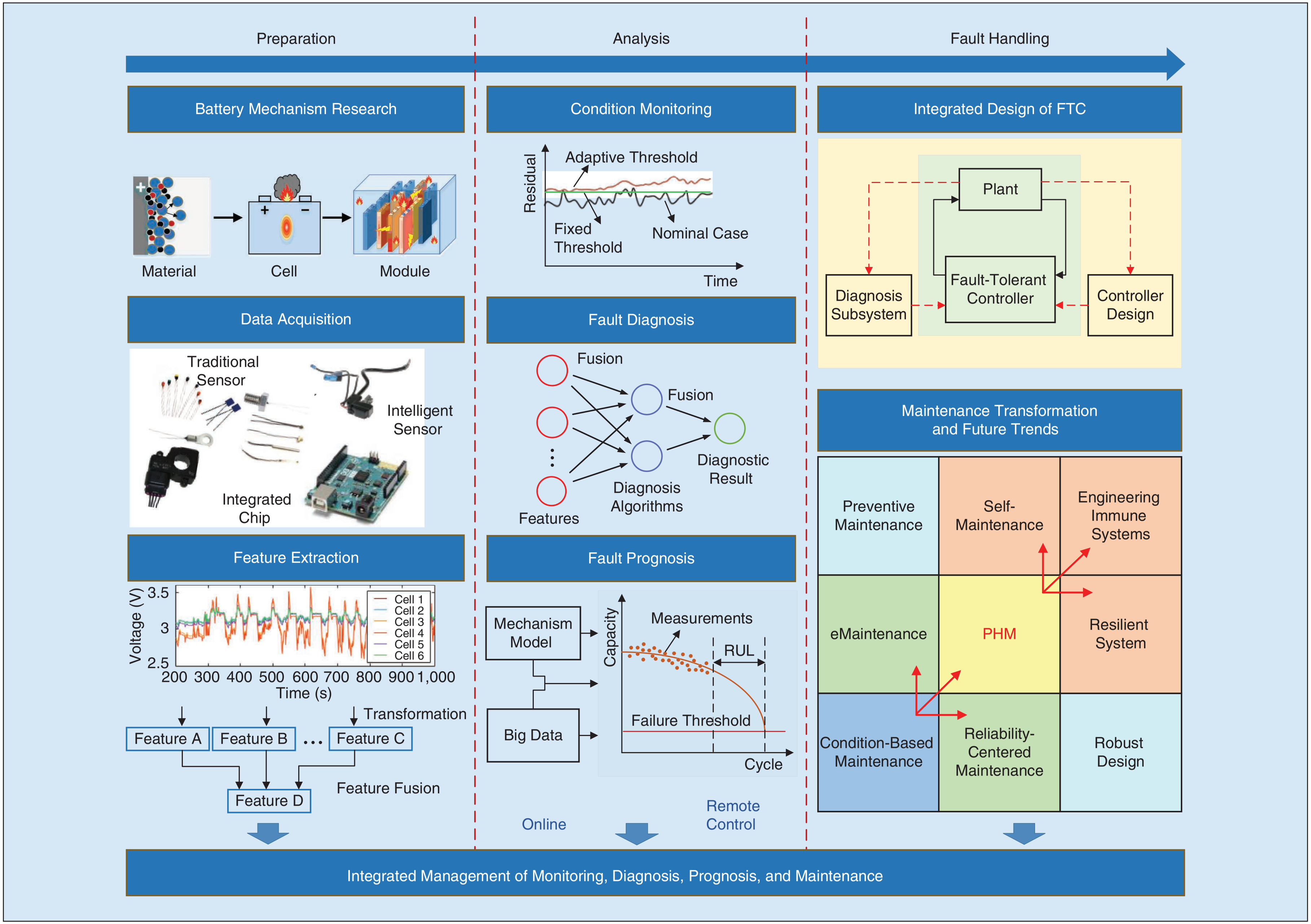

FIGURE 10 – The prospects of fault diagnosis technology for Li-ion battery systems. Adapted from [179]. PHM: prognostics and health management; RUL: remaining useful life.

Battery faults have different modes, complex mechanisms, and coupled relationships among themselves.

the safety of a battery system. The thresholds play a significant part in the tradeoff between the sensitivity and the robustness for model-based fault diagnosis. Generally, the threshold is affected by a variety of factors, including modeling errors, random disturbances, and system inputs and outputs. The accuracy of the condition monitoring and the fault diagnosis can be improved by developing an adaptive threshold that takes into account battery aging and usage patterns.

The model-based state estimation and parameter estimation methods are still commonly used in the fault diagnosis of LIBSs. In comparison with the knowledge-based and data-driven methods, the model-based method is more suitable for fault isolation and fault size estimation, due to its full utilization of battery system dynamics. For a safer battery system, fault isolation must be included, which identifies and locates a specific fault from battery, sensor, and actuator faults. Besides, due to the significant impacts on the fault severity analysis and subsequent countermeasures, fault estimation should also be considered as an important research topic.

Note that the imbalance of the battery capacity, SOC, and internal resistance are often ignored in many existing studies. Therefore, future investigations should also consider this important factor, especially for battery pack applications. Methods that are robust to battery inconsistency, such as the correlation coefficient technique, are expected to be directly used for battery pack fault diagnosis and as a preprocessing technique for machine learning diagnostic methods.

With the advent of the era of big data, data-driven methods are expected to promote the rapid development of battery system fault diagnosis. However, a single fault diagnosis algorithm has an inherent limitation, and it is often difficult to achieve the desired effect. Therefore, a research trend in fault diagnostics is to fuse multiple fault features and diagnostic algorithms, further improving the overall performance of the diagnostic system. For some faults with a slow evolution process, such as a spontaneous ISC, early fault diagnostics and prognostics will play an increasingly vital role in ensuring the safety of the battery system. Based on the physics-centered model and big data, combining knowledge and data will very likely become an inevitable trend for the next generation of intelligent battery diagnostics.

Fault-Handling Stage

In the fault-handling stage, rapid and efficient actions targeting identified battery system faults, such as FTC and necessary maintenance, are critical for maintaining the safe operations of a LIBS. Currently, the controller and fault diagnosis subsystems are usually designed separately. It is a potentially promising research topic to develop a fault-tolerant controller that integrates both. Although the PHM for rotating machinery systems have been developed and discussed in [179], research into battery system maintenance is still in its infancy. Given the complexity and the poor maintainability of a battery system, it is also an important topic to develop the PHM system.

Currently, the fault diagnosis development for the battery system is shifting from offline to online, from local single-machine control to network-based remote control. The integrated management of monitoring, diagnosis, prognosis, and maintenance across the entire life span of a battery would be a future trend in the development of fault diagnostics for LIBS.

Conclusion

This article provides a comprehensive survey on the fault mechanisms, fault features, and fault diagnosis of various faults in LIBSs, including internal battery faults, sensor faults, and actuator faults. The goal is to promote a comprehensive understanding of the latest technologies and stimulate innovative ideas for LIBS fault diagnosis.

None of the reviewed diagnostic methods is the one-size-fits-all solution for different faults in a battery system. Battery faults have different modes, complex mechanisms, and coupled relationships among themselves. These faults typically result in abnormal changes in the estimated battery state and model parameters such as the capacity, internal resistance, SOC, and temperature. Therefore, model-based state estimation and parameter estimation have become the most common methods for battery fault diagnosis.

Developing high-fidelity battery models can improve the performance of model-based methods. For example, since battery aging has an important impact on the diagnostic performance, it is important to establish an electro–thermal–aging coupling model and to update the model parameters online. There are fewer machine learning-based methods in battery diagnostics because a large amount of fault data for a LIBS is not easily available. With the advent of the era of big data, data-driven methods are expected to play an increasingly important role in LIBS fault diagnosis. However, a single fault diagnosis method has inherent limitations, and it is a promising trend to combine multiple fault features and diagnostic methods to further improve the accuracy and robustness of LIBS diagnostics.

Sensor and actuator faults are often treated as unknown input signals and model parameter deviations, respectively. Since such faults do not involve electrochemical information about a battery, a simple ECM is sufficient for the diagnostic requirements in the model-based method. More research work on model-based methods should focus on improving the detection sensitivity of early faults as well as the robustness against model uncertainties, unknown disturbances, and noises. For data-driven methods, the entropy method is particularly suitable for detecting battery connection faults by capturing the degree of disorder of signals with abnormal fluctuations. Model-based methods capture detailed battery system dynamics and are therefore more suitable for fault isolation and fault size estimation. These methods can be used for FTC and subsequent countermeasures.

For the fault diagnosis of a battery pack, the differences in the voltage, temperature, estimated capacity, SOC, and internal resistance between cells can be taken as effective fault features. Battery fault detection and even short circuit current estimation can be performed based on the MDM of a battery pack, with state estimation and parameter estimation. However, these model-based methods are affected by cell inconsistencies in a battery pack. Therefore, more data-driven methods that are robust against battery inconsistencies, such as the correlation coefficient method, should be developed for LIBS fault diagnosis. Battery fault diagnosis in parallel-connected battery strings remains a challenge, and a better sensor placement design and advanced diagnostic algorithms are needed to solve this problem.

In conclusion, the fault diagnostics of LIBSs is still at an early stage. Battery fault mechanisms under special conditions, such as fast charging, should be further investigated. For some slowly evolving faults, such as spontaneous ISCs, early fault diagnostics and prognostics will play an increasingly important role in ensuring the safety of a battery system. In practice, standardized substitute tests for LIBS faults need to be developed for diagnostic algorithm validation and diagnostic technology development.

Thresholds play a significant role in the tradeoff between the sensitivity and robustness of fault diagnosis. The accuracy of condition monitoring and fault diagnosis can be improved by developing adaptive thresholds that take into account battery aging and usage patterns. In addition, most studies on battery, sensor, and actuator fault diagnosis are based on the assumption that other components are fault-free, and therefore multifault detection and isolation in battery systems is still a challenging issue. To summarize, advanced LIBS fault diagnosis needs further research on 1) multiscale mechanism studies at the material, cell, and pack levels; 2) development of battery models and diagnostic methods that can be implemented in practical applications; and 3) multifault diagnostics, early fault diagnostics and prognostics, and FTC for battery packs.

With the advent of the era of big data, data-driven methods are expected to play an increasingly important role.

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Biographies

Xiaosong Hu (xiaosonghu@ieee.org) earned his Ph.D. degree in automotive engineering from the Beijing Institute of Technology in 2012. He performed scientific research and completed his Ph.D. dissertation at the Automotive Research Center, University of Michigan, Ann Arbor, between 2010 and 2012. He is currently a professor at the State Key Laboratory of Mechanical Transmissions and in the Department of Automotive Engineering, Chongqing University, China. His research interests include modeling and controlling alternative powertrains and energy storage systems. He has been a recipient of several prestigious awards/honors, including the Highly Cited Researcher Award from Web of Science in 2019, Society of Automotive Engineers Ralph R. Teetor Educational Award in 2019, Emerging Sustainability Leaders Award in 2016, European Union Marie Currie Fellowship in 2015, American Society of Mechanical Engineers Dynamic Systems and Control Division Energy Systems Best Paper Award in 2015, and Beijing Best Ph.D. Dissertation Award in 2013. He is a Senior Member of the IEEE.

Kai Zhang (kaizhang@cqu.edu.cn) earned his B.Eng. degree in engineering and technology from Southwest University, Chongqing, China, in 2016. He is currently pursuing a Ph.D. degree in the College of Automotive Engineering, Chongqing University, China. His research interests include the fault diagnosis of batteries, sensors, and actuators in lithium-ion battery systems.

Kailong Liu (kailong.liu@warwick.ac.uk) earned his B.Eng. degree in electrical engineering and his M.Sc. degree in control theory and control engineering from Shanghai University, China, and his Ph.D. degree in electrical engineering from the Energy, Power, and Intelligent Control group, Queen's University Belfast (QUB), United Kingdom, in 2011, 2014, and 2018, respectively. He is a research fellow in the Warwick Manufacturing Group, University of Warwick, United Kingdom. His research interests include modeling, optimization, and control, with applications to electrical/hybrid vehicles, energy storage, and battery management systems. He was the student chair of the IEEE QUB Student Branch and a recipient of awards including the Engineering and Physical Sciences Research Council Scholarship, Santander International Scholarship, and QUB Engineering Science and Mechanics International Scholarship. He is a Member of the IEEE.

Xianke Lin (xianke.lin@uoit.ca) earned his B.S. degree from Zhejiang University, China, in 2009, and his Ph.D. degree in mechanienginering from the University of Michigan, Ann Arbor, in 2014. He is

an assistant professor in the Department of Automotive, Mechanical, and Manufacturing Engineering, University of Ontario Institute of Technology, Oshawa, Canada. His research activities concern hybrid powertrain design and control strategy optimization, multiscale/multiphysics modeling, and the optimization of energy storage systems. He is a Member of the IEEE.

Satadru Dey (satadru.dey@ucdenver.edu) earned his M.S. degree in controls from the Indian Institute of Technology Kharagpur in 2010 and his Ph.D. degree in automotive engineering from Clemson University, South Carolina, in 2015. He is currently an assistant professor of electrical engineering at the University of Colorado, Denver. His research interests include the control of energy and transportation systems. He has worked on several projects related to batteries, ultracapacitors, electric vehicles, and connected and autonomous vehicles. He is a Member of the IEEE.

Simona Onori (sonori@stanford.edu) earned her Laurea (summa cum laude) degree in computer science engineering from the University of Rome "Tor Vergata," Italy, in 2003, her M.S. degree in electrical and computer engineering from the University of New Mexico, Albuquerque, in 2004, and her Ph.D. degree in control engineering from the University of Rome "Tor Vergata" in 2007. She has been an assistant professor in the Energy Resources Engineering Department and Director of the Stanford Energy Control Lab, Stanford University, California, since October 2017. She is the recipient of numerous awards including the 2019 Board of Trustees Award for Excellence from Clemson University, 2018 Global Innovation Contest awarded by LGChem, 2018 Society of Automotive Engineers Ralph R. Teetor Educational Award, 2017 National Science Foundation Career award, 2017 Clemson University College of Engineering and Science Dean's Faculty Fellows Award, and 2017 Clemson University Esin Gulari Leadership and Service Award. She is a Senior Member of the IEEE.

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