Proceedings of CONF-MLA 2026 Symposium: Learning and Decision Making in Multi Agent Software Systems
DOI: 10.54254/2755-2721/2026.BA36186

A Review of Current Approaches to Fault Diagnosis in Lithium-Ion Batteries

Shunpang Zeng

Guangdong Country Garden School, Foshan, China
zeista_work@outlook.com

Abstract. In the age of rapid digital transformation, electric vehicles have become more and more common, and have gradually displaced the status of diesel. It is essential for people to pay more attention to the safety of lithium batteries. To illustrate, a lithium-ion battery is prone to error under long-term charging or discharging and high temperature. If the fault diagnosis is not at the right time, it might lead to the declining performance of the lithium-ion battery and shorten the servicing life. This study aims to discuss the technologies for detecting the error in lithium batteries, which are categorized into three forms: Model-based method, Signal processing-based method and Machine learning method. Meanwhile, these technologies have been widely applied in the area of electric vehicle and battery management systems, detecting the state of batteries in real-time. Overall, this study considers that there are no any fault diagnosis methods that are suitable for all the application scenarios, and researchers should choose the approach according to their needs. The future development trend is the combination of various fault diagnosis techniques, improving the accuracy, reliability and performance.

Keywords: lithium-ion battery, fault diagnosis, model-based method, signal processing-based method, machine learning

1. Introduction

Lithium batteries have become the key components of electric vehicles [1], which impact the safety, lifetime and cost of EVs to a certain extent [2]. What makes error-detection of lithium batteries so important? Fire is one of the primary reasons. As the circuit inside the battery experiences a short circuit, the temperature will surge dramatically, leading to an instant burning rate in the battery. Therefore, an explosion may happen, which is more complex than a regular fire disaster. In functional consideration, When the car has detected a high-voltage error or abnormal temperature, it will directly cut down the power. So, the car will lose motivation, and if it is happened on a high-speed road, a rear-ending event might happen.

This paper presents a comprehensive review of fault detection techniques for lithium-ion battery, with a focus on three mainstream methods: model-based method, signal processing-based method and machine learning method. This study will illustrate the basic principle of these three methods, comparing their advantages and limitations according to accuracy, reliability and practical

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applicability. By comparison, researcher is being convenience from choosing the appropriate method according to their needs, improving their system's reliability and safety.

2. Battery management system

Battery management system (BMS) is acting the brain that connects battery and the car. It is responsible to monitor in real-time about the battery state, ensuring the battery is operate within a safe and efficient operating window, and as much as possible to extend the service life of battery. A standard BMS includes several functions: Voltage monitoring (prevent overcharging and overdischarging), Temperature monitoring (Prevent overheating from triggering thermal runaway), Cell balancing (Maximize usable capacity of battery), State of charge estimation (estimate the remaining power), State of health estimation (assess degree of aging), Fault diagnosis (Monitor the error in real-time). Fault diagnosis is one of the key functions of BMS, which categorized into three major approaches: Model-based method, Signal processing-based method and machine learning method.

2.1. Fundamentals of lithium batteries

The battery is the component that converts the chemical energy into electric energy [3]. For the lithium battery, there are usually four components, which are the cathode, anode, separator and electrolyte (Figure 1). To explain, the cathode is made up of lithium transition metal oxide, and it is able to release lithium-ion during charge and receive lithium-ion during discharge. As for the anode, it usually consists of graphite, which is function at store the lithium-ion that are migrated from cathode during charge; separator is the microporous separator membrane between the cathode and anode, physically blocking the conduction between them and prevent short circuit. Meanwhile, it is allowed for the lithium-ion to transmit freely; electrolyte is a chemical medium that is filled inside the battery, providing a channel for transmitting lithium-ion between the cathode and anode. Furthermore, the principle of lithium-ion can be considered as the movement of lithium-ion between the cathode and anode. When discharging, the lithium atom inside the anode loses the electron and becomes a lithium-ion and enters the electrolyte. Then, while the lithium-ion transmits the separator into the cathode, electrons have been flowing into the cathode through the external circuit, which becomes current for charging finally. As for the charging process, the external charger forces the electron flow from cathode to anode by using high voltage, and the lithium-ion escapes from the cathode, getting back to the anode and intercalating into the graphite for storing energy.

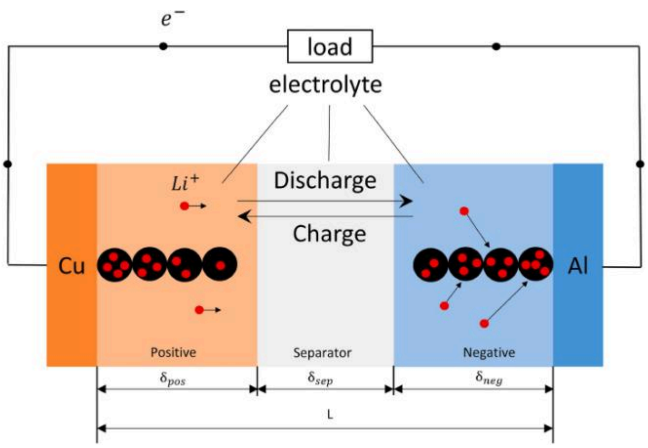

Figure 1. Schematic diagram of electrichemical model for lithium-ion batteries [4]

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2.2. Common battery faults

In the long-term running, the lithium-ion battery may be erred by different faults. In this case, timely identification and detection of these faults are crucial for ensuring the safety of the battery and extending its service life. To illustrate, the battery faults are classified as 5 different types: overcharging, overdischarging, internal short circuit, overheating and capacity degradation. Specifically, overcharging happens when the charging voltage or current exceeds the rated limit, causing a structural degradation of the cathode material, decomposition of the electrolyte and gas generation, which in sinister cases can trigger thermal runaway and fire. In contrast, overdischarging the battery below the cut-off voltage can cause dissolution of the negative electrode current collector and the formation of copper dendrites, leading to permanent capacity loss and even internal short circuit during subsequent charging. An internal short circuit can be caused by internal defects or mechanical puncture. It leads to intense heating and is one of the most dangerous triggers of thermal runaway in batteries. Overheating is triggered by excessively environmental temperature, which will accelerate battery aging; a capacity degradation is happened by the combined results of active lithium loss, electrode material aging and increase internal resistance, which will present a lower driving range and decreased charging efficiency.

3. Research methods

3.1. Model-based method

Model-based method detects faults by comparing measured values with the model output. The difference between the two is known as residual [5] (Equation 1).

$$\text{Residual} = \text{Measured value-estimated value} \tag{1}$$

Specifically, measured value are obtained directly through physical sensor measurements, while estimated values are generated indirectly via mathematical algorithms. The system is only normal when the residual is close to 0, which means values apart from 0 indicate different abnormal reasons. When the residual is positive, it represents that the voltage, current or temperature might have one that is higher than the estimated one. As for the negative residual, it displays the possibility that voltage, current or temperature may be lower than the estimated one. It is important to determine whether the residual is exceeding the threshold value, which fault might occur. Subsequently, there are four major methods that are included in the model-based method. The Equivalent Circuit Model (ECM), a simplified model structure that is easy for parameter identification, is imitating the battery through voltage sources, resistors and capacitors [6]. Although ECM is widely adopted due to its high computational efficiency, its lack of physical depth inevitably leads to an increase in error; the electrochemical model, a method that combines physics and chemistry, is used to simulate the trajectory of lithium-ion. While it provides a high precision, it requires a complex computation. An auto-adjustable method known as Kalman filter, it combining the data from other models in previous time steps to predict the current state [7]; lastly, the Recursive Least Square is an online algorithm that upgrades the model according to the new pass-on data.

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3.2. Signal processing-based method

In contrast, the signal processing-based method directly analyzes the data (voltage, current and temperature) collected by the sensor instead of setting up the complex physical or chemical models. To illustrate, when a battery experiences a fault, the output signal of voltage and current will usually present a fluctuation or noise. The key to this method is to extract the abnormal signal that is beneath the normal one by using mathematical tools like the time domain, frequency domain or time-frequency domain. In this analysis, signal conversion is necessary, which usually utilizes methods like Fourier transform, Wavelet transform and Entropy calculation. Specifically, the Fourier transform is a means to convert the signal into different frequencies of sine waves [8]. Therefore, any complex signal that varies over time can be represented as a superposition of series sine waves (different frequency, amplitude, and phase) (Figure 2). The time domain focuses on how the signal changes by the time, whereas the frequency domain focuses on what the signal consists of. Although the Fourier transform is able to tell what frequency is contained during the period, it is unable to tell when a specific frequency occurs because it assumes the signal is stationary. Since a battery fault is a non-stationary signal, the Fourier transform easily loses critical temporal information; as for the wavelet transform, it is a microscope that combines the time domain and frequency domain.

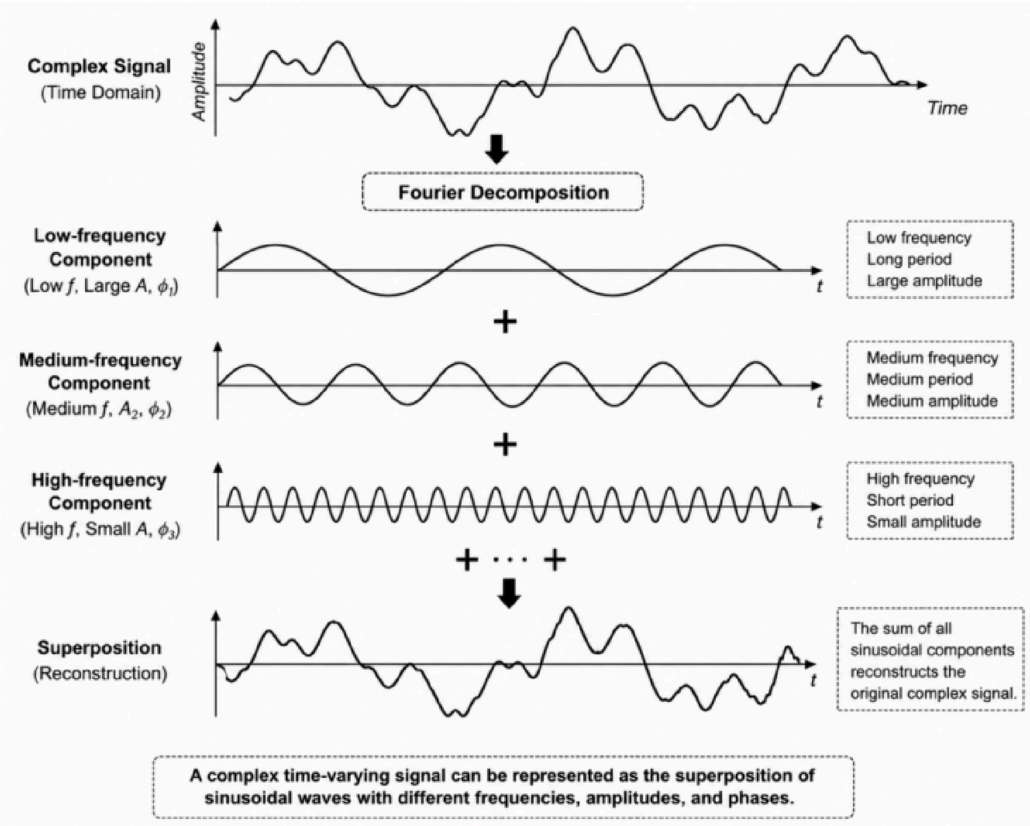

Figure 2. Fourier decomposition for complex signal

To address the drawback of the Fourier transform of losing critical temporal information, the wavelet transform has introduced a window function, which utilizes short, decaying wavelets to match and scan the signal [9]. The advantages of the wavelet transform are its capability for multi-resolution analysis: For high-frequency signal (noise), using a narrow time window to achieve high time resolution and accurately locate the exact occurrence of a fault; for the low-frequency signal, it

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adopts a wide time window to achieve high-frequency resolution and accurately analyze the trend. For instance, when the battery experiences a micro-short-circuit, the terminal voltage experiences a brief, sharp downward peak, which can be highlighted on the time-frequency spectrum. In addition, when the wavelet transform decomposes the signal into high frequency and low frequency, it can filter out high-frequency noise to reconstruct a clean signal; furthermore, the entropy calculation is used to measure the randomness and complexity [10]. For the error signal, it will fluctuate dramatically and have high randomness, which means a significant increase in the entropy. Overall, while the signal processing-based method benefits from no need for complex modelling and high sensitivity to transient faults, it is limited by the lack of physical interpretability and the high requirement of sampling rate.

3.3. Machine learning method

Machine learning is driven by data, as the algorithm can learn by itself from the historical data, figuring out the relationship between the input data (voltage, current, temperature and time) and the output data (SOC, SOH and error type) [11]. To be specific, machine learning is categorized into two types: traditional machine learning and deep learning. Traditional machine learning requires humans manually extract some features; the model will train by these features. It typically applied for the battery error classification: Classify and identify whether the battery has experienced a micro short circuit, sensor fault or loose connection. For deep learning, this method enables end-to-end learning. For instance, by directly feeding time-series voltage and current data into the network, the model can automatically extract deep temporal features, eliminating the need for laborious manual feature processing. Therefore, this enables it to apply in long-term SOC/SOH estimation: as the LSTM possesses a time-memory function, it is able to process these dynamic time-series data, and capture the capacitive effects and nonlinear dynamics. There are several advantages of the machine learning method; one of the benefits is the strong nonlinear mapping capability: In a lithium-ion battery, there exists a strong nonlinearity and time-varying dynamics for the internal reaction, aging mechanism and thermal characteristic. In addition, it is suitable for the cloud-BMS and big data analytics: As the increasing on-board BMS networking provides massive fleet operating data, it is an excellent fuel for machine learning. The more data there is, the higher the generalization ability of the model and accuracy. However, there is a lack of explanation due to the black-box nature. Specifically, the decision made by the neural network is hard to explain using physical theory, which is a potential risk in the car industry that demands high security. Moreover, there is a robust data dependency: if the training data does not cover the situation, such as extreme low temperature or high charging rate, then the battery will behave worse when it encounters in reality. Although machine learning benefits from its high accuracy and nonlinear and adaptive capabilities, it requires a large dataset and high computation.

4. Comparisons

Table 1. Comparison of different strategies

Aspect	Model-based	Signal Processing	Machine learning
Principle	Mathematical model	Signal analysis	Data-driven
Accuracy	High	Medium	High

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Table 1. (continued)

Computation	Medium	Low	High
Explainability	Excellent	Moderate	Poor
Data Requirement	Low	Low	Very High
Real-time Performance	Good	Excellent	Depends

Nowadays, ECM is still widely adopted in BMS, as it succeeds in the balance between computational efficiency, diagnostic accuracy and implementation cost (Table 1). Furthermore, the Signal processing-based method is especially suitable for the transient faults because they provide multi-resolution ability to analyze, filter out noise and highlight the weak fault features. Moreover, machine learning is often considered as the most promising approach in the future. Its primary reason is the conversion from manually designed rules to machine learning patterns directly from data. There has been an exponential increase in the available dataset, which will enhance machine learning over time. Therefore, different methods are suitable for different fault diagnosis scenarios rather than replacing each other.

5. Conclusion

This paper reviewed the fault diagnosis techniques for lithium-ion batteries used in electric vehicles. Three categories of method, namely the Model-based method, the Signal processing-based method and the machine learning method, were introduced and compared form the perspectives of their principals, advantages and limitations. The Model-based method is strong at interpretability and suitable for real-time BMS, while the Signal processing-based method is sensitive to the transient faults and able to filter out the noises. Finally, machine learning has a high accuracy but requires a massive dataset. None of these methods is universally superior, and the choice depends on practical application requirements. Future research is expected to focus on hybrid diagnosis that combines the model-based method and artificial intelligence, thereby improving the accuracy, robustness and reliability of battery fault diagnosis. Moreover, the development of a cloud-based battery management system provides opportunity for large-scale data collection and model updating. Data from thousands of vehicles can be continuously updated to cloud servers, allowing diagnostic models to learn from diverse operating conditions and improve their generalization ability. Lastly, future battery fault diagnosis systems are expected to achieve higher real-time performance while maintaining low computational cost, making them more suitable for embedded battery management systems. Meanwhile, the experimental data, fault types, evaluation metrics and test environments adopted by different studies vary considerably, making it difficult to execute a fair comparison between different fault diagnosis methods. Therefore, it is essential to establish a standardized datasets and test platforms in order to more objectively evaluate different approaches.

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