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# Review of Research on Fault Diagnosis of Electric Vehicle Battery System

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**Abstract:** The safety and reliability of electric vehicles (EVs) are pivotal factors influencing the development of the industry. Malfunctions in power batteries constitute a primary cause of fire incidents in EVs, rendering the research of advanced fault diagnosis technology for power battery systems a critical focus within the domain of EV safety. This paper endeavors to provide a systematic review of the extant research on fault diagnosis of EV battery systems. Initially, it delineates common fault types, underlying causes, and possible consequences within battery systems. Subsequently, it classifies and synthesizes the existing fault diagnosis methodologies. On this foundation, the principal challenges encountered in the current research on fault diagnosis technology for power battery systems are examined. Ultimately, the prospective development trajectories for fault diagnosis technology in EV battery systems are prognosticated, aiming to provide references for theoretical advancements and technological innovations, thereby fostering the progressive evolution of the EV industry.

**Keywords** Electric vehicle; Power battery system; Fault diagnosis; Data-driven

## INTRODUCTION

With the advancement of technology and economic development, issues such as energy structure and environmental pollution are receiving increasing attention. As a cornerstone industry of the international economy, the automotive sector possesses a substantial driving force, and electric vehicle (EV), as a key representative of the new energy industry, play a crucial role in achieving "carbon peak and carbon neutrality". Batteries, the core components of EVs, provide the essential power for operation, and their operational status directly impacts the overall vehicle performance. Power batteries generally consist of battery cells, battery modules, and battery packs, which are assembled through series and parallel connections of numerous cells. This extensive interconnection increases system complexity and the heterogeneity among cells escalates the risk of various faults, potentially leading to fire hazards [Huang Y *et al.*, 2021]. Consequently, accurate identification, rapid localization, and early warning of EV battery faults are critically important, emphasizing the significance of research on EV battery fault diagnosis technologies.

This paper first introduces the fault types and causes of power batteries, reviews the research progress of current fault diagnosis technologies for power batteries, summarizes the challenges in existing power battery fault diagnosis technologies, and anticipates future research directions in battery fault diagnosis technologies. The goal is to provide valuable references for future research endeavors and contribute positively to further exploration and development in this field.

## COMMON FAULTS OF POWER BATTERIES

As critical components of EVs, battery performance is influenced by various factors such as energy density, design defects, cycle life, improper operation, and harsh environmental conditions. The fault types are complex and diverse. Understanding fault types and mechanisms facilitates rapid and accurate fault diagnosis. Common battery systems mainly consist of the battery body, connection components, sensors, thermal management system, and battery management system (BMS) [Yang J *et al.*, 2022]. During actual operation, any component of the battery system may fail. Based on whether the fault is directly related to the battery itself, faults can be broadly categorized into two types: battery body faults and non-battery body faults, as shown in Table 1.

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Table 1. Faults of Power Battery Systems for Electric Vehicles

| Fault Component | Fault Type | Underlying Causes | Possible Consequences |
|---|---|---|---|
| Battery Body Faults | Capacity degradation | High-temperature environment<br>Over-charging, over-discharging | Reduced range<br>Shortened lifespan |
| | Internal resistance increase | Electrode material aging<br>High-temperature expansion | Decreased cycle life<br>Increased risk of thermal runaway |
| | Thermal runaway | Long-term aging<br>Thermal abuse<br>Mechanical abuse | Increased risk of fire and explosion |
| | Short circuit | Growth of metal dendrites piercing the separator<br>Electrolyte leakage<br>Internal water ingress<br>Insulation layer degradation | Battery damage<br>High exothermic reaction<br>Fire hazard |
| Non-Battery Body Faults | Connector component faults | Battery installation defects<br>Strong vibration environment<br>Corrosion and gas expansion | Terminal melting<br>Thermal runaway<br>Decreased capacity and power performance |
| | Sensor faults | Manufacturing defects<br>Vibration and shock | Misjudgment of battery status<br>Affecting battery performance |
| | Battery management system faults | Balancing component faults<br>Charge/discharge control component faults<br>Temperature control component faults | Increased battery inconsistency<br>Overcharging/discharging<br>Reduced lifespan<br>Thermal runaway |
| | Thermal management system faults | Abnormal cooling and preheating temperature management | Fire and explosion<br>Decreased battery performance |

## FAULT DIAGNOSIS TECHNOLOGIES OF POWER BATTERIES

Currently, the predominant fault diagnosis technologies for EV batteries can be categorized into knowledge-based, model-based, and data-driven approaches.

### Knowledge-Based Fault Diagnosis Technologies

Knowledge-based fault diagnosis methods for battery systems primarily rely on domain experts' prior knowledge and rules. With the continuous advancement of technology, knowledge-based methods have integrated various artificial intelligence technologies, analyzing large amounts of historical data to extract underlying knowledge related to system variables. These methods then use classifiers to compare observed system dynamics with the knowledge base for accurate diagnostic decisions [Zhao Z *et al.*, 2022]. Knowledge-based fault diagnosis technologies include expert systems and graph theory methods.

The expert system method is widely used in fault diagnosis, and its core components include a knowledge base, inference engine, real-time database, and human-machine interface. This method performs fault inference and judgment by matching fault characteristics with fault labels in the knowledge base and continuously improves the knowledge base through learning and knowledge accumulation. The inference engine is a key component of the expert system, typically employing fuzzy logic methods to predict fault types. Wu J R (2011) applied fuzzy mathematics theory to establish a fuzzy diagnostic matrix through fuzzy comprehensive evaluation, incorporating manual fault exclusion functions in the inference engine to enhance accuracy. Wu C, Zhu C, and Ge Y (2017) employed similar methods to establish a diagnosis system based on fuzzy logic, providing detailed descriptions of fault symptoms and linking them to internal fault mechanisms. Cao Y, Zhou Z J, Hu C H, et al. (2021) proposed a single attribute approximate belief rule and constructed a new expert system ABRB, solving BRB rule explosion and weak scalability issues by reducing attribute correlation. Zhao S (2021) utilized fuzzy theory to analyze battery fault mechanisms, calculating fault memberships and verifying diagnostic accuracy using BP neural network, RBF neural network, and support vector machine.

Graph theory methods include fault tree analysis and directed graph-based fault diagnosis. The fault tree-based diagnosis method begins from the system's fault state, performing step-by-step reasoning to determine root causes, impact levels, and fault probabilities. Yang M (2023) analyzed the main categories of power battery faults and established a power battery fault tree based on 16 existing domestic standards [Yang M, 2023]. With technological advancements, fault tree analysis has been combined with intelligent algorithms. Zhang C, Fang W, Zhao B, et al. (2022) developed a UB+ fault tree model by thoroughly analyzing automotive power supply fault principles. By mapping the fault tree to a Bayesian network, they constructed a fuzzy Bayesian network model for UB+ faults. Directed graphs are widely used to describe causal relationships in systems. Zhang W and Jiang L (2023) established a directed graph model for power battery systems at the module level, achieving module-level fault localization and conducting simulation experiments.

Knowledge-based fault diagnosis methods exhibit significant advantages when applied to EV battery systems, including not relying on precise mathematical models and extensive calculations, high accuracy, strong interpretability, good flexibility, and cost savings on data. However, they also have drawbacks such as high knowledge acquisition and maintenance costs, limited applicability, inability to handle uncertainties, and lack of adaptability.

### Model-Based Fault Diagnosis Technologies

Model-based fault diagnosis technologies for batteries operate by establishing mathematical models to describe the dynamic behavior of battery systems based on physical or electrochemical principles. The estimated values obtained from model predictions are compared with real-time monitored battery performance parameters, such as voltage, current, and temperature. The differences serve as data support for fault diagnosis, further analyzing fault information. Battery model types include equivalent circuit models (ECM), electrochemical models, thermal models, and electro-thermal models [Hu X *et al.*, 2017]. Model-based methods encompass state estimation, parameter estimation, parity equations, and structural analysis.

Equivalent circuit models simulate the dynamic voltage characteristics of batteries using circuits composed of components such as capacitors and resistors. Multiple equivalent circuit models have been utilized to capture different fault modes, estimating terminal voltage with strong tracking extended Kalman filters (ST-EKF) and generating residual signals online to effectively detect various battery fault scenarios. Wei J, Dong G, and Chen Z (2019) employed multiple equivalent circuit models to capture different fault modes, estimated terminal voltage with ST-EKF, and generated residual signals online to effectively detect various battery fault scenarios. Ge Y L, Chen Z Q, and Zheng C W (2018) based on a first-order equivalent circuit model, included battery parameters in state variables, combined with an unscented transform strong tracking filter (UTSTF) algorithm to estimate battery parameters in real-time for fault diagnosis. This method efficiently tracks and diagnoses battery fault parameters in variable temperature environments. Electrochemical models establish dynamic equations for electrodes and electrolytes based on internal reaction mechanisms, simulating internal battery conditions. Wu W, Qiao D, Wang X, et al. (2024) constructed a multi-physical domain internal short circuit model based on electrochemical mechanism models, revealing the electro-thermal characteristics of early internal short circuit faults by simulating different internal short circuit resistances.

Temperature is one of the most critical factors affecting battery performance, safety, and lifespan, making thermal model research highly valuable. Thermal models include single-state lumped parameter thermal models [Dey S *et al.*, 2016], dual-state lumped parameter thermal models [Dey S *et al.*, 2016], and partial differential equation distributed parameter thermal models [Dey S *et al.*, 2017]. Due to the complex electrochemical processes in batteries, temperature and electrical parameters influence each other and are highly coupled, necessitating electro-thermal coupled models for simulation analysis. Identifying the residual signals of core temperatures to detect battery faults. Wei J, Dong G, and Chen Z (2019) combined electro-thermal models with Lyapunov methods for observer-based thermal fault detection. Li X, Lyu M, Gao X, et al. (2023) proposed a method combining particle swarm optimization algorithms and recursive least squares for electro-thermal models, achieving real-time diagnosis of thermal faults and thermal parameters. Bai X, Peng D, Chen Y, et al. (2024) proposed an electro-thermal-magnetic coupled model to quickly and accurately detect internal short circuits, determine dendrite locations, and assess crack conditions [Bai X *et al.*, 2024].

### Data-Driven Fault Diagnosis Technologies

With the development of artificial intelligence technology, data-driven fault diagnosis technologies have gradually become a research focus. The principle is to collect and preprocess data during battery operation, using signal processing techniques like wavelet transform [Yao L *et al.*, 2020], spectrum analysis [Xue Q *et al.*, 2021], and modal decomposition [Zheng J *et al.*, 2023] to obtain key features, combining statistical analysis and machine learning for training and validation, ultimately achieving fault diagnosis, localization, real-time monitoring, and predictive fault evaluation [Wu M *et al.*, 2023].

Statistical analysis methods are based on statistical information of cleaned operational data, heuristically determining information thresholds through parameters like information entropy, wavelet packet decomposition results, and single cell voltage correlation coefficients to identify faults. Lin T, Chen Z, and Zhou S (2022) used the correlation coefficient method, considering the impact of inconsistency in resistance and state of charge on the correlation coefficient, improving diagnosis accuracy and speed. Zhang X, Hong J, and Xu X (2023) used entropy algorithms to extract diagnostic entropy values and proposed a robust and universal multi-level diagnostic strategy. Sun J, Chen S, Xing S, et al. (2024) combined incremental capacity curve analysis with extended Kalman filtering, improving the accuracy of internal short circuit fault diagnosis and resistance and SOC estimation.

Wang G, Jin S, Jiao J, et al. (2024) proposed a principal component analysis method combined with an adaptive threshold and sliding window technology with fusion factors for internal short circuit fault diagnosis of lithium-ion batteries, significantly reducing false alarm rates through adaptive updates [Wang G *et al.*, 2024].

Machine learning methods train black-box models with large amounts of data, continuously adjusting models to minimize errors, maximizing the practical operation of batteries to diagnose faults. Wang J, Wu X, Zhao D, et al. (2023) proposed a method combining whale optimization algorithm optimizing variational mode decomposition and particle swarm optimization optimizing support vector machine for internal short circuit fault diagnosis of lithium-ion batteries, effectively improving fault recognition rates. Li S, Zhang C, Du J, et al. (2022) used a two-dimensional feature clustering method based on signal decomposition and DBSCAN, effectively distinguishing defective cells from normal battery packs. Jiang J, Li T, Chang C, et al. (2022) used the isolated forest algorithm to detect abnormal information in dynamic components, improving the prediction capability of progressive and sudden faults by decomposing voltage data into static and dynamic components through signal processing. Sun J, Ren S, Shang Y, et al. (2023) proposed a fault prediction method based on convolutional neural networks and long short-term memory networks, achieving high prediction accuracy and reliability in real data validation of lithium-ion batteries. Huang Z, Su J, Xie B, et al. (2024) proposed a fault diagnosis algorithm combining fuzzy C-means clustering and probabilistic neural network, significantly improving classification accuracy. With technological progress and increased practical demands, fusion algorithms have gradually become a research hotspot [Song Y *et al.*, 2024].

## SUMMARY AND OUTLOOK

### Summary

Current battery fault diagnosis algorithms have achieved good diagnostic effects to some extent but still have the following shortcomings:

1) Knowledge-based fault diagnosis technologies: Most batteries diagnose faults by setting thresholds, with uncertainties regarding the threshold values, involving expert experience, the matching degree of threshold rules with actual scenarios, and fixed thresholds cannot meet the needs of precise fault diagnosis for nonlinear time-varying systems Integrated multiple design methods (top-down, bottom-up, centralized and distributed architecture, etc.)

2) Model-based fault diagnosis technologies: Although there are various battery models, the internal battery is a complex electrochemical process. The same fault may have multiple causes, and multiple faults may be coupled, requiring in-depth exploration and analysis of fault mechanisms for precise fault diagnosis, along with real vehicle data.

3) Data-driven fault diagnosis technologies: While highly accurate, they are greatly influenced by samples. Currently, real vehicle data is scarce and difficult to collect, limiting the application of algorithms in actual scenarios. Additionally, there is insufficient research on algorithm performance balance, with many internal parameters, making it difficult to achieve a balance between accuracy, timeliness, robustness, and complexity through simple trial and error.

### Outlook

To address the current issues in battery fault diagnosis algorithms, the following prospects for future research are proposed:

1) Hybrid model-based fault diagnosis algorithms: Combining expert knowledge bases and threshold rules to identify simple faults, building models based on internal mechanisms to improve accuracy, and using neural networks and other data-driven technologies to enhance adaptability, comprehensiveness, and robustness, enabling quick and accurate fault diagnosis and early warning.

2) Establishing coupled electrochemical models: Future research should focus on diagnosing multi-parameter coupled faults, starting from the internal electrochemical mechanisms of batteries, comprehensively considering the coupling effects of various parameters, establishing more precise coupled models, and achieving accurate diagnosis and localization of complex faults.

3) Integrating artificial intelligence technologies: To address low accuracy in real vehicle applications, establishing full lifecycle monitoring and diagnostic algorithms, collecting real vehicle data, real-time monitoring battery status, and achieving precise fault early warning. To address poor algorithm performance balance, integrating AI technologies for parameter optimization, enhancing the algorithm's adaptive learning ability, providing early warning, and proposing corresponding handling solutions, reducing maintenance costs.

4) Real-time fault diagnosis integrating cloud and edge computing: The integration of big data analysis and AI algorithms is a development trend in electric vehicle battery fault diagnosis. Utilizing 5G technology and big data analysis to accurately grasp big data characteristics, improving data transmission speed and algorithm processing speed. Additionally, the application of digital twin technology in electric vehicles makes remote, efficient, and precise diagnosis possible.

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