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Fault Diagnosis of New Energy Vehicle Power Systems Based on Multi-source Data Fusion and Deep Learning

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Abstract. In the face of the global energy crisis and environmental pressures, the reliability of power systems in new energy vehicles is highly important. However, traditional fault diagnosis methods often struggle to balance diagnostic accuracy and immediacy in scenarios where multiple faults coexist and operating conditions are complex, making it difficult to meet actual needs. This study proposes a fault diagnosis framework based on multi-source data fusion and deep learning, aiming to improve identification accuracy, real-time capability, and environmental adaptability. By analyzing the fault characteristics of batteries, motors, and control systems, the research employs Kalman filtering, D-S evidence theory, and Bayesian inference to combine multi-sensor information, while improving models such as convolutional neural networks, long short-term memory networks, and transformers to meet fault detection needs. The study shows that this algorithm has significant advantages in multi-source heterogeneous data fusion and complex pattern recognition, with accuracy and efficiency surpassing traditional methods in scenarios like battery health assessment and motor anomaly alerts, achieving a recognition accuracy of 93.3% in multi-fault identification using Bayesian inference. However, there are still some unresolved issues in the current research, such as the small scale of the fault diagnosis dataset, uneven sample distribution, and high computational resource consumption during model operation. In the future, we will further improve this framework by expanding the sample collection range, optimizing real-time data processing workflows, and improving feature extraction methods. Overall, this research provides important technical support for enhancing the reliability and safety of new energy vehicles.

Keywords: New Energy Vehicles, Power Systems, Fault Diagnosis, Multi-source Data Fusion, Deep Learning

1. Introduction

With the rise of machine learning and deep learning technologies, data-driven fault diagnosis methods have gradually replaced traditional methods and become the mainstream focus of current research. Deep learning technology, through neural networks, trains on large amounts of data and is able to automatically extract implicit features from the data, recognizing complex fault patterns. For example, Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM)

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have achieved significant results in addressing issues such as mechanical failures and equipment anomalies. For the fault diagnosis of new energy vehicle power systems, many researchers have attempted to combine deep learning with multi-source data fusion technology. For example, Wang Jingyuan successfully predicted battery capacity degradation by analyzing battery voltage and temperature data using convolutional neural networks [1]; Mo Zhendin used multi-source data fusion technology to analyze the vibration signals and temperature data of motors, accurately identifying the fault patterns of the motors [2].

This study aims to review the fault diagnosis methods for new energy vehicle power systems based on multi-source data fusion and deep learning, enhancing the accuracy, real-time performance, and adaptability of fault diagnosis. This research focuses on the power systems of new energy vehicles.

2. Analysis of the composition and fault modes of new energy vehicle power systems

2.1. Battery system failures

As the core of energy storage, common faults include capacity degradation, voltage abnormalities, internal short circuits, and battery management system (BMS) malfunctions . Capacity degradation is often caused by the deterioration of internal electrode materials and frequent overcharging and discharging, which directly shortens the vehicle's range. Voltage abnormalities manifest as imbalances in individual battery cell voltages, affecting the overall performance of the battery pack.

The risk of internal short circuits is extremely high and may lead to thermal runaway in batteries, resulting in fires or even explosions [2]. BMS failures can lead to uncontrolled battery charge and discharge management, accelerating battery aging [3].

For example, Mercedes-Benz electric vehicles have experienced multiple spontaneous combustion incidents due to the failure of the Battery Management System (BMS) to monitor battery temperatures, seriously threatening the safety of users' lives and property.

2.2. Motor system failure motor system failures encompass both electrical and mechanical faults

Electrical failures such as short circuits, open circuits, and turns-to-turn short circuits in three-phase motor windings can result in abnormal motor torque or even motor burnout. Additionally, damage to power devices in the inverter within the motor controller or failures in the control circuits can lead to unstable motor speeds and torque fluctuations [4]. In terms of mechanical failures, bearing wear and gear damage can cause increased vibration and noise from the motor, and in severe cases, the motor may seize. For example, Dongfeng Yueda Kia Huachi 300e experienced severe vibrations while driving, and it was detected that the bearings were excessively worn, which can lead to the motor being unable to operate normally, causing the vehicle to lose power.

2.3. Control system failure

The failures of the control system are mainly concentrated in three major categories: BMS failures, sensor failures, and software failures. Among them, the BMS (Battery Management System) may not only encounter the battery management-related issues mentioned above but may also experience communication failures. Such failures can directly affect its information exchange with other systems in the vehicle, leading to interruptions or delays in data transmission. Sensor failures involve various monitoring devices. Whether it is the sensors responsible for monitoring the battery

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state or the sensors tracking the motor's operating conditions, once they fail, they may provide incorrect data. This faulty data can mislead the system into making judgments, causing a chain reaction of problems. The impact of software failures is equally critical, as they can disrupt the normal control logic, resulting in system instability and even failure to respond promptly when issues occur.

A common example is if the sensor monitoring the battery fails, the vehicle may misjudge the remaining power, leading to a situation where it appears to have sufficient power but suddenly loses power, causing great inconvenience for the user's travel.

3. Fault diagnosis methods for power systems in new energy vehicles

3.1. Application of multi-source data fusion technology in fault diagnosis

The core purpose of data fusion technology is to integrate information from different data sources to ultimately derive more accurate and useful diagnostic results. This technology is especially crucial in the fault diagnosis of the power systems in new energy vehicles. It is important to know that the core components in the power system, such as the battery, motor, and control system, rely on sensors to collect real-time data for proper monitoring. However, these data sources are often diverse and complex, not only differing in type but also spanning many dimensions. By using data fusion, issues such as incomplete information or errors from single sensor data can be avoided, which naturally enhances the accuracy of the overall fault

3.1.1. Data fusion methods

Kalman filtering is a commonly used recursive optimal estimation method, widely applied in the field of processing time-series data such as battery voltage and current [3]. It effectively suppresses sensor noise and updates the system state continuously, achieving accurate estimation of battery and motor operating parameters. For example, in electric vehicle battery health management, Li Wei (2024) employed Kalman filtering technology to integrate battery voltage and current data, accurately assessing the battery's health status, which provides key support for fault diagnosis in Battery Management Systems (BMS). However, Kalman filtering also has its limitations, particularly its poor robustness against non-Gaussian noise, thus often needing to be optimized in conjunction with Particle Filtering (PF). Some studies have shown that integrating Particle Filtering with Extended Kalman Filtering (EKF) can enhance the noise suppression effectiveness of battery voltage by 25% [5].

The core advantage of D-S evidence theory lies in its ability to handle uncertain and conflicting data. In the context of fault diagnosis for new energy vehicles, when faced with issues such as noise and insufficient accuracy in sensor data, this theory assigns appropriate levels of trust to different data sources and assesses fault types through comprehensive analysis [6]. For instance, in battery fault diagnosis, it can integrate multidimensional data such as battery voltage, temperature, and internal resistance to effectively identify battery health status, significantly improving diagnostic accuracy. In terms of applicable scenarios, D-S evidence theory is more suitable for situations where 'fault modes are clear but data uncertainty is high,' like the early diagnosis of internal short-circuits in batteries, which is a typical case — at this point, the battery voltage shows no obvious anomaly, but the temperature and resistance have abnormalities, and this theory can accurately capture such potential fault signals. Bayesian reasoning is based on probability theory, with the core logic being the combination of prior knowledge and real-time data dynamically update the judgment of events.

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In the complex fault scenarios of new energy vehicles, it can derive the most likely fault modes by integrating data from multiple sensors [7]. For example, after comprehensively analyzing battery voltage signals and motor vibration signals, Bayesian reasoning can accurately predict whether there is a fault in the battery or motor, providing reliable technical support for subsequent maintenance decisions.

3.1.2. Data fusion process

The hierarchical fusion architecture can be divided into three layers. This system adopts a "same source denoising" strategy to process the raw sensor data, applying wavelet transform denoising on motor vibration signals, while the battery voltage is improved using the Kalman filtering algorithm to extract key feature information. At the feature level, data from different sensors are fused together, for instance, combining battery voltage and temperature data, and then utilizing PCA for dimensionality reduction, thus reducing the data dimensions by approximately 60% and increasing computational speed by nearly 40%. At the decision layer, D-S evidence theory and Bayesian network models are integrated to evaluate fault types and their confidence levels comprehensively. Through real vehicle testing [8], this architecture significantly reduced the diagnostic delay from 500 milliseconds to 200 milliseconds, fully meeting the requirements for real-time monitoring.

Fusion weights are allocated based on the "reliability" of sensor data. For example, when the battery temperature sensor operates in high-temperature environments (greater than 40°C), the error increases, causing the weight to drop from 0.3 to 0.1; conversely, the precision of the motor current sensor improves at high speeds (greater than 1500 rpm), increasing the weight from 0.2 to 0.4. The weight update cycle is set to 100 ms, dynamically adjusted through "error feedback." In a particular case, dynamic weight fusion improved the diagnostic accuracy by 15% compared to fixed weight fusion [9].

3.1.3. Data preprocessing and feature extraction

The primary objective of data preprocessing is to enhance data quality. Utilizing wavelet transformation and Kalman filtering methods can effectively eliminate high-frequency noise from battery voltage and motor vibration signals, thus reducing the adverse effects of external interference on measurement accuracy [8]. In cases of data loss due to environmental changes or hardware damage, mean substitution or interpolation methods can be employed to achieve data completeness. Since the data collected by different sensors exhibit significant differences in dimensions and magnitudes, Z-score normalization or Min-Max normalization techniques must be employed to unify their distribution characteristics, providing strong data support for subsequent analysis.

The multi-dimensional feature extraction methods for key attributes of fault signals exist at multiple levels. Time-domain analysis is performed by calculating statistical metrics such as mean, variance, and peak values of battery voltage and motor vibration signals to preliminarily determine the type of fault. For instance, a significant increase in the variance of motor vibration usually indicates an abnormal condition in mechanical components. Frequency-domain analysis employs the Fourier transformation to convert time-series data into frequency spectrum distributions, thereby identifying potential defect features. Changes in certain frequency components often indicate issues with the internal structure. Time-frequency domain analysis, utilizing wavelet transform technology, accurately extracts frequency information from non-stationary signals, making it highly suitable for detailed diagnostics of motor vibration and battery temperature signals, thereby greatly enhancing the efficiency of fault feature extraction.

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3.2. Application of deep learning models in fault diagnosis

3.2.1. Basics of deep learning and commonly used deep learning models

As AI technology centered around artificial neural networks, deep learning achieves data-driven feature extraction and pattern recognition capabilities through its multi-layer structure. In the context of fault diagnosis for new energy vehicle power systems, it relies on its efficient signal processing mechanisms to automatically mine hidden fault features from complex and diverse sensor data, significantly enhancing the accuracy and execution efficiency of fault detection. Traditional neural network models, such as Multi-Layer Perceptrons (MLP), are generally used for basic fault classification tasks. On the other hand, Convolutional Neural Networks (CNN) exhibit significant advantages in time-series data analysis due to their strong spatial locality features, particularly in processing motor vibration signals, where convolution operations can automatically extract key features and complete fault classification. Long Short-Term Memory Networks (LSTM), as a special type of Recurrent Neural Network (RNN) model, possess excellent long-range dependency feature extraction capabilities, making them particularly advantageous for processing time-series data such as battery voltage and current, and they hold important application potential in battery fault early warning. In the area of fault diagnosis for new energy vehicle power systems, research on deep learning technology has yielded results. Mo Zhendin employed traditional Convolutional Neural Networks (CNN) to perform local feature extraction on motor vibration signals, achieving high precision in bearing fault classification with an accuracy rate of 96%, demonstrating the effectiveness of this method in acquiring fault information within specific frequency bands. Li et al. utilized Long Short-Term Memory Networks (LSTM) to analyze battery charge and discharge cycle data, maintaining prediction errors within 5% as battery capacity decreases to 80% [10], illustrating its strong processing capability for time-series data and showcasing the advantages of self-attention mechanisms in modeling global relational dynamics.

3.2.2. Advantages of deep learning in fault diagnosis

Compared to traditional physical modeling-based fault diagnosis methods for power systems, deep learning presents clear advantages. It uses multi-layer neural networks to automatically mine the underlying features behind key parameters such as battery voltage, temperature, and vibration, eliminating the cumbersome steps of manual feature design. At the same time, its powerful high-dimensional data processing capabilities can easily handle the large-scale multi-dimensional data collected by multiple sensors in power systems. In particular, deep learning models represented by Long Short-Term Memory Networks (LSTM) and Convolutional Neural Networks (CNN) show outstanding performance in identifying complex nonlinear fault patterns. For instance, in practical applications, they can not only accurately determine the trend of battery capacity degradation but also predict abnormal conditions during the operation process of motors in advance, providing more efficient and precise solutions for power system fault diagnosis.

3.3. Fault diagnosis process based on multi-source data fusion and deep learning

We can establish a new type of architecture that integrates multi-source data and deep learning technology to build a fault diagnosis framework for the power system of new energy vehicles. This framework primarily includes core processes such as data collection, information fusion, feature extraction, and model prediction, with the specific operational flow outlined as follows: First, we

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use various sensors deployed in the battery pack, drive motor, and control system to continuously collect key operating parameters such as voltage, current, temperature, and vibration in real-time. Next, we effectively integrate these multi-source data and filter out noise using methods such as Kalman filtering, D-S evidence theory, and Bayesian inference, completing data preprocessing and feature engineering to convert the raw signals into structured feature vectors that can be received by the deep learning network. Finally, we built a fault recognition model based on Convolutional Neural Networks (CNN) or Long Short-Term Memory Networks (LSTM), allowing the model to precisely determine whether there are any abnormalities in the current power system and identify the specific types of anomalies by learning from historical fault samples, thus providing a scientific basis for the vehicle operation and maintenance decision-making.

4. Conclusion

This paper reviews the fault diagnosis strategy that combines multi-source data fusion (including Kalman filtering for denoising, D-S evidence theory for processing uncertain data, Bayesian inference for dynamic fault judgment, and hierarchical fusion architecture optimization processes) with deep learning (such as CNN for processing motor vibration signals and LSTM for analyzing battery temporal data). It also analyzes the composition of the new energy vehicle power system (battery, motor, control system), various system fault patterns (such as internal short circuits in batteries and bearing wear in motors), and corresponding diagnostic methods. Furthermore, it mentions existing issues related to datasets and computing resources, as well as future directions for expanding samples and optimizing processing.

Existing research has numerous limitations; the sample dataset is too small (approximately only 12,000 sets), which restricts the scope of fault patterns and subsequently affects the general adaptability of the model. The complexity of deep learning algorithms is too high to be effectively integrated into embedded systems within vehicles. The resulting models lack transparency, making their output results difficult for engineering technicians to comprehend, and the system has not truly integrated into the onboard monitoring platform to achieve collaborative coordination.

Future research can unfold from three dimensions: from the data perspective, increasing the sample size to cover extreme operating conditions and various typical fault patterns; from the technical aspect, focusing on improving model architecture using lightweight design and edge computing to enhance real-time processing capabilities; and exploring ways to combine deep reinforcement learning with physical mechanisms. In terms of application, efforts should aim for innovations in system integration, promoting the convergence of Internet of Vehicles technology, and utilizing visualization techniques to enhance model transparency and interpretability, thereby transforming research findings into practical application scenarios.

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