REVIEW ARTICLE

Current Status and Trend Analysis of Motor Fault Diagnosis

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Abstract

As the core power equipment and primary load in power systems, electric motors are involved throughout the entire power generation, transmission, substation, and distribution processes. Their operational reliability directly determines the safety and stability of the power grid. This paper provides a systematic analysis of the current status and future trends in motor fault diagnosis. Specifically, it summarizes the three mainstream approaches currently used in motor fault diagnosis: model-based methods, signal processing-based methods, and artificial intelligence-based methods, while highlighting the respective advantages and application limitations of each approach. The analysis reveals three prominent challenges in existing research: inefficient multi-source information fusion, difficulties in early weak fault detection, and insufficient stability in decision-making integration. Future research directions are identified, including mechanism-data dual-driven strategies, deep cross-dimensional feature fusion of current, vibration and temperature signals, denoising algorithms for faint fault features, and edge-based online diagnostic systems for full-life predictive health management. It clarifies that overcoming the limitations of single-domain analysis, establishing an efficient fusion framework, and enhancing adaptability to complex operating conditions are crucial for further improving diagnostic accuracy and ensuring reliable operation of motors and power supply systems.

Keywords: motor, fault diagnosis, current status, trend analysis.

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1 Introduction

As the core power equipment and main load of the power supply system, motors run through the whole process of power generation, transmission, substation and distribution, and their operational reliability

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directly determines the safety and stability of the power grid [1–3]. Common motor faults include stator short circuit, rotor eccentricity, bearing damage, etc. A single fault is likely to cause temperature rise and intensified vibration, which will further develop into electromechanical compound faults, leading to equipment shutdown, system paralysis, and threatening production safety and economic operation.

2 Current Status of Motor Fault Diagnosis

At present, motor fault diagnosis technology has formed three mainstream research directions: analytical model-based method, signal processing-based method, and artificial intelligence-based method, each with advantages and limitations.

2.1 Analytical Model-Based Diagnosis Method

This method establishes mathematical relationships among motor state parameters and identifies faults by comparing the error between predicted output and actual output. Reference [4] proposed an inter-turn short-circuit fault detection method based on the DC component in the negative-sequence current residual under the synchronous rotating coordinate system. Reference [5] reconstructed fault detection index and fault phase location index based on the second harmonic component in the squared modulus of the current residual vector, and put forward a robust detection and location method for inter-turn short-circuit faults of permanent magnet synchronous motor (PMSM) based on the squared modulus of the current residual vector. The analytical model-based diagnosis method relies on the mathematical mechanism model of motors and realizes fault judgment by comparing the deviation between actual operating parameters and theoretical model parameters. It is applicable to standardized industrial scenarios with stable motor operating conditions, clear working mechanisms and complete parameter data. This method features solid physical logic and high diagnosis accuracy, and can achieve precise fault localization and quantitative analysis without massive historical data. However, it highly depends on accurate motor mathematical models and well-matched equipment parameters and working conditions. It has poor adaptability to complex nonlinear operating conditions and aged and inaccurate equipment, resulting in weak generalization performance and low universality.

2.2 Signal Processing-Based Diagnosis Method

This method extracts fault features in the time and frequency domains by collecting current, vibration, magnetic flux, temperature, and other signals. Common techniques include Fourier transform, wavelet transform, Hilbert–Huang transform, empirical mode decomposition, etc. It has the advantages of convenient signal acquisition and fast diagnosis speed. Chen et al. [6] established an inter-turn short-circuit fault model for internal PMSMs and applied wavelet transform to extract second-harmonic voltage features for fault diagnosis. Zeng et al. [7] proposed installing detection coils on each stator tooth to obtain tooth magnetic flux signals, and used high-order harmonics generated by inverters to diagnose inter-turn short-circuit faults. Building on this approach, Zeng et al. [8] further extended the stator tooth flux method to online rotor fault diagnosis of permanent magnet synchronous motors.

The signal processing-based diagnosis method identifies faults by extracting time-domain and frequency-domain features of vibration, current, temperature and other signals. It is suitable for offline and online routine detection of various conventional motors. This method features strong practicability, fast response and low cost, and requires no complex mechanism modeling, which is conducive to practical engineering application. Nevertheless, it highly relies on manual feature extraction and empirical judgment. It presents insufficient ability to identify incipient weak faults and compound coupled faults and is susceptible to environmental noise, resulting in a low degree of diagnosis intelligence and automation.

2.3 Artificial Intelligence-Based Diagnosis Method

As a current research hotspot, this method realizes fault classification by simulating manual judgment through algorithms such as neural network, support vector machine (SVM), convolutional neural network (CNN), and gradient boosting decision tree. Reference [9] developed a non-contact fault diagnosis system for bearings using discrete wavelet transform for signal denoising and support vector machines for fault classification, demonstrating the effectiveness of SVM-based approaches in motor-related mechanical component diagnosis. Reference [10] directly took raw thermal infrared images as input and effectively identified rotor system faults using an improved CNN. Reference [11] proposes an intelligent motor multi-fault diagnosis method based on wide kernel convolutional neural

Table 1. The comparison of three types of motor fault diagnosis methods.

Comparison Dimension	Analytical Model-based Diagnosis Method	Signal Processing-based Diagnosis Method	Artificial Intelligence-based Diagnosis Method
Basic Principle	Relies on the mathematical mechanism model of the motor, realizes fault judgment by comparing the deviation between the actual operating parameters and the theoretical parameters of the model, and is modeled based on the physical mechanism.	Extracts the time-domain, frequency-domain and time-frequency domain features of motor vibration, current, temperature and other signals, identifies faults through feature analysis, and does not require complex mechanism modeling.	Relies on big data and deep learning algorithms, automatically mines fault features in motor operation data, realizes end-to-end fault identification and diagnosis, and does not require manual feature extraction.
Typical Technologies	State space model, equivalent circuit model, Kalman filter, parameter identification method, fault tree analysis	Fourier transform, wavelet transform, Hilbert-Huang transform, envelope analysis, spectral analysis, time-frequency analysis	BP neural network, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Random Forest
Applicable Fault Types	Conventional faults with clear mechanism and measurable parameters, such as motor stator/rotor winding faults, bearing faults, air gap eccentricity, permanent magnet demagnetization, etc.	Conventional mechanical and electrical faults such as motor bearing faults, gearbox faults, rotor broken bars, air gap eccentricity, winding short circuits, etc., suitable for offline/online routine detection	Incipient weak faults, multi-fault coupling, compound faults under complex nonlinear working conditions, hidden faults without clear mechanism, suitable for intelligent operation and maintenance under complex working conditions
Core Advantages	Strong physical logic, high diagnosis accuracy, capable of precise fault location and quantitative analysis, no need for a large amount of historical data, and strong interpretability	Strong practicability, fast response speed, low cost, no need for complex mechanism modeling, low threshold for engineering implementation, and suitable for routine detection scenarios	No need for manual feature extraction, strong generalization ability, capable of accurately identifying incipient weak faults and compound faults, suitable for complex nonlinear working conditions, and capable of realizing intelligent and automatic operation and maintenance
Main Limitations	Extremely dependent on the accurate mathematical model of the motor, high requirements for the matching degree of equipment parameters and working conditions, poor adaptability to complex nonlinear working conditions, the diagnosis accuracy drops significantly after the equipment is aged and out of alignment, and the generalization ability is weak	Highly dependent on manual feature extraction and empirical judgment, insufficient ability to identify incipient weak faults, poor diagnosis effect on compound coupled faults, susceptible to environmental noise interference, and low degree of diagnosis intelligence	Dependent on a large amount of high-quality labeled datasets, low diagnosis accuracy in small-sample scenarios, poor algorithm interpretability, high hardware computing power and data collection costs, and long model training and iteration cycle
Engineering Application Challenges	Motor parameter drift and working condition fluctuation in industrial sites lead to model mismatch, requiring frequent model calibration; it is difficult to model non-standard customized motors, making it difficult to achieve large-scale application	The strong noise environment in industrial sites makes it difficult to extract signal features, requiring complex noise reduction preprocessing; manual feature extraction relies on expert experience and is difficult to standardize and replicate	High-quality fault labeled data in industrial sites is scarce, making model training difficult; the black-box nature of the algorithm leads to low trust in industrial scenarios and difficulty in meeting safety and compliance requirements; the computing power cost of edge deployment is high, and real-time performance is difficult to guarantee

networks, integrating multi-source signals to address severe noise interference and insufficient fault feature extraction under complex operating conditions. Reference [12] proposes a fault diagnosis method integrating EMHFDE, RFE and NGO-LSSVM. Reference [13] develops a SCADA-based wind turbine fault diagnosis framework combining Gramian angular field encoding, CNN, LSTM and Kolmogorov–Arnold network to handle coupled nonstationary signals. Reference [14] proposes a hybrid diagnosis method integrating multi-level wavelet decomposition, gated recurrent and fully convolutional networks for ship synchronous generator terminal short-circuit faults. Reference [15] proposes a hybrid intelligent scheme combining DWT, statistical screening and dual-branch 1D-CNN to fuse vibration and current for induction motor fault diagnosis. These approaches demonstrate the growing trend toward data-driven fault diagnosis, where feature engineering is minimized and deep learning models extract discriminative patterns autonomously. However, challenges remain in generalizing across operating conditions and ensuring robustness to noise. Recent efforts focus on hybrid architectures that combine physical model insights with deep representations to improve interpretability and reliability.

The artificial intelligence-based diagnosis method automatically mines fault features via big data and deep learning algorithms, which is applicable to intelligent operation and maintenance scenarios with complex working conditions, coupled multiple faults and massive operating data. It eliminates manual feature extraction and possesses strong generalization ability, enabling accurate identification of incipient weak faults and compound faults to meet the demands of intelligent and automatic operation and maintenance. However, it relies heavily on massive high-quality labeled datasets, resulting in low diagnosis accuracy under small-sample conditions. In addition, the algorithm has poor interpretability and requires high hardware computing power and data collection costs.

The comparison of core dimensions of the aforementioned three types of motor fault diagnosis methods is shown in Table 1.

3 Trend Analysis of Motor Fault Diagnosis

Although remarkable progress has been achieved in existing research, three prominent problems remain. First, the fault information content of multi-source signals varies greatly; single-domain feature extraction is difficult to achieve efficient fusion, and decision-level fusion cannot fully utilize data complementarity, limiting diagnosis accuracy and generalization ability.

Second, early fault features are weak; complex working conditions and motor parameter variations mask fault information, and commutation current distortion of brushless DC motors further interferes with feature extraction, making early identification challenging.

Third, decision-level fusion is mostly applied to models with similar characteristics, lacking sufficient heterogeneous cross-model integration, which limits the ability to characterize multi-dimensional mathematical properties and reduces classification stability.

Overall, motor fault diagnosis is developing toward multi-domain feature extraction, multi-source information fusion, deep learning driving, and early weak fault identification.

4 Conclusion

This paper systematically reviews the progress and application characteristics of three mainstream motor fault diagnosis methods: analytical modeling, signal processing and artificial intelligence. The analytical model method features clear physical logic and no requirement for massive data, yet it suffers from parameter drift and equipment aging, leading to poor performance under complex conditions and for incipient faults. The signal processing approach is easy for practical implementation and extracts features via time-frequency analysis, but it relies heavily on manual experience and struggles to identify weak incipient and coupled composite faults. Artificial intelligence combined with multi-source information fusion has become a research hotspot due to automatic feature extraction; nevertheless, existing data-level, feature-level and decision-level fusion frameworks have respective defects, and single-signal, single-layer fusion limits diagnostic accuracy and generalization.

Comprehensive analysis reveals three common drawbacks: inadequate fusion of multi-source heterogeneous data, early fault features masked by operational noise, and insufficient diversified cross-model decision fusion. Future research should adopt the mechanism-data dual-driven strategy to integrate motor physical principles and multi-sensor big data, realize deep cross-dimensional feature fusion of current, vibration and temperature signals via deep learning, develop denoising algorithms for faint fault features to eliminate interference from commutation distortion and working fluctuation, explore heterogeneous model decision fusion, construct edge-based online diagnostic systems, and shift motor maintenance from breakdown repair to full-life predictive health management.

Data Availability Statement

Not applicable.

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Conflicts of Interest

Zheng Fang is affiliated with the State Grid Zhejiang Lishui Power Supply Company, Lishui 323000, China. Yongbo Lu and Binsheng Li are affiliated with the Zhejiang Julihuang Industrial Technology Co., Ltd, Jinyun 321404, China. The authors declare that these affiliations had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

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The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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