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A Review of Marine Engine Fault Diagnosis Technology

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Abstract: This review focuses on marine engine fault diagnosis technology, systematically organizing and analyzing fault diagnosis methods for ship engines and gas turbines. It elaborates on the application of automation and digitalization technologies in ship engine fault diagnosis, as well as various data-driven, thermodynamic model-based, and knowledge-based diagnostic methods for gas turbines. Practical case studies demonstrate the effectiveness of these technologies, while current challenges are discussed, and future development directions are outlined, aiming to provide a comprehensive reference for research and practice in this field.

Keywords: Marine Engine Fault Diagnosis, Ship Engine, Gas Turbine, Automation, Digitalization, Data-Driven, Thermodynamic Model, Knowledge-Based Diagnosis.

1. Introduction

As the core power system of ships and numerous industrial equipment, the safety and reliability of marine engines are of paramount importance. Faults can not only lead to production interruptions and significant economic losses but may also cause severe safety accidents, endangering human lives. With the rapid development of the shipping industry and increasing demands for power equipment in industrial sectors, the structure and operating conditions of marine engine systems have become increasingly complex, raising the probability of faults. Therefore, in-depth research and development of efficient and accurate marine engine fault diagnosis technologies have become critical for ensuring normal equipment operation, reducing maintenance costs, and improving production efficiency. This paper provides a comprehensive review of fault diagnosis technologies for ship engines and gas turbines, analyzing the characteristics, application cases, existing problems, and future trends of current technologies.

2. Ship Engine Fault Diagnosis Technology

2.1. Basic Principles of Fault Diagnosis

The core of gas turbine fault diagnosis lies in utilizing advanced signal processing and data analysis techniques, combined with physical models and empirical knowledge, to establish a mapping relationship between equipment operating states and fault characteristics. Signal acquisition is the starting point of the diagnostic process, requiring high-precision sensors to monitor key parameters such as vibration, temperature, and pressure. The collected data must have high sampling rates and low noise to ensure information integrity. The feature extraction stage employs time-domain, frequency-domain, or time-frequency-domain methods to extract fault-related indicators, such as root mean square values, power spectral density, and wavelet energy. Feature selection should ensure high relevance and independence of variables based on the specificity of equipment structure and fault modes. State identification is performed using classification algorithms or predictive models, with common methods including support vector machines (SVMs), neural networks, and deep learning models[1].

2.2. Application of Automation and Digitalization in Ship Engine Fault Diagnosis

With rapid technological advancements, automation and digitalization technologies are playing an increasingly important role in ship engine management and fault diagnosis. Chen Yixing, in "Research and Analysis on the Transformation of Ship Engine Technology Management Based on Automation and Digitalization," pointed out that automated ship engine management technology forms a complete automated control system by applying automation techniques to engine systems. This system uses sensors and actuators to acquire and control engine data and operations, achieving real-time monitoring and adjustments through digital programming and algorithms to ensure safe and efficient engine operation[2].

In engine system control, sensors collect real-time data, which is transmitted to the automated control system via feedback control systems. The latter adjusts control parameters and actuators in real time to maintain the system within preset operating conditions. Meanwhile, remote monitoring and control systems enable managers to understand engine status and perform remote operations anytime, anywhere, improving the timeliness and accuracy of fault diagnosis.

Digital ship engine management technology leverages advanced information technology and data analysis methods to upgrade traditional management approaches to digital models. By designing the integration and hierarchy of the transformation, digital systems are divided into SaaS, PaaS, and IaaS layers, enabling real-time monitoring of engine status, data analysis and decision support, fault diagnosis and prediction, and maintenance plan optimization. In engine data acquisition and analysis, digital technology achieves efficient and automated data collection, utilizing big data storage and cloud computing for data management and analysis. Data analysis algorithms and machine learning techniques uncover patterns in the data, providing valuable information for fault diagnosis. In fault diagnosis and predictive maintenance, digital technology assists managers in accurately diagnosing faults and predicting maintenance needs through real-time monitoring and diagnostic systems, data analysis and decision support, predictive maintenance strategies, remote fault diagnosis and support, and maintenance records and knowledge bases, thereby improving equipment reliability and availability[3].

2.3. Key Points of Ship Engine Inspection and Fault Repair Technology

Zhang Hefei, in "Research on Key Points of Ship Engine Inspection and Fault Repair Technology," used diesel engines as an example to elaborate on ship engine inspection points and fault repair techniques. For diesel engine inspection, the cylinder head and liner, as components with concentrated thermal loads, require special attention to the radial wear of the liner and the roughness of the inner surface. When radial wear exceeds 0.4% of the original size or the inner surface roughness (Ra) exceeds 1.6 μm, repairs or replacements are necessary. Additionally, the cooling water passages must be checked for blockages. For pistons and connecting rods, the wear of the first and second ring grooves should be measured. If the wear exceeds 15% of the original height, the piston rings must be replaced. The piston cooling cavity and skirt should also be inspected. For connecting rods, the wear of the big and small end bushings and the bolt preload torque must be measured. The inspection of the crankshaft and main bearings focuses on measuring journal and bearing wear, crankshaft bending and ovality, as well as main bearing clearance and oil film thickness. Bearings must be replaced when wear reaches specified standards. The inspection of the fuel and lubrication systems includes checking the wear and sealing of high-pressure fuel pumps and injectors, as well as the degree of oil filter clogging and oil degradation[4].

For typical diesel engine faults, such as cylinder scuffing and cylinder explosion, specific repair techniques are available. Cylinder scuffing, often caused by poor lubrication, can be repaired using copper infiltration technology, where a copper-based coating is deposited on the worn surface via electroplating to restore performance. Cylinder explosion, resulting from abnormal combustion, can be addressed using laser cladding repair technology, where high-energy laser beams coat metal powder on the substrate to form high-performance alloy coatings for repairing critical components like crankshafts. Additionally, remanufacturing forming technology and additive remanufacturing technology are employed. The former combines welding technology with remanufacturing to repair and upgrade components like pistons, while the latter uses a "bottom-up" material accumulation manufacturing mode to remanufacture diesel engine cylinder heads, improving component performance and lifespan.

2.4. Common Types of Marine Engine Equipment Faults

Ship engine equipment faces various fault risks during long-term operation, including bearing wear and gear damage in rotating machinery, as well as seal leakage and corrosion damage in fluid machinery. Bearing wear manifests as increased vibration amplitude and enhanced specific fault frequency components in the spectrum. Wear severity can be detected using envelope demodulation analysis and time-frequency analysis. Gear faults, such as tooth breakage or pitting, cause non-stationary characteristics in impact signals, requiring impact response analysis and wavelet transform for feature extraction. Pump seal leakage typically leads to reduced operational efficiency and fluid pressure fluctuations, which can be detected by monitoring the inlet and outlet pressure difference in real time. The salty and humid marine environment accelerates corrosion damage to engine equipment, requiring visual inspection and ultrasonic thickness measurement for diagnosis[5].

2.5. Current State of Fault Diagnosis Technology Development

Modern fault diagnosis technology has evolved from traditional vibration analysis to multi-modal data fusion and intelligent diagnosis. Traditional methods primarily rely on monitoring single physical quantities, which are suitable for common fault modes but lack accuracy and adaptability in complex and variable operating environments. Intelligent diagnosis methods based on big data and artificial intelligence have become a research focus, as they can automatically extract complex features using deep neural networks, overcoming the limitations of manual feature selection. Convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) exhibit excellent performance in processing non-stationary signals and long time-series data. Future technological developments aim to achieve real-time and adaptive diagnostic systems by optimizing sensor placement and data transmission architectures, as well as developing lightweight and embeddable intelligent algorithm models to meet the operational complexity and safety requirements of ship engine equipment[6].

3. Gas Turbine Fault Diagnosis Technology

3.1. Data-Driven Diagnostic Methods

Data-driven gas path fault diagnosis methods analyze fault states by acquiring gas turbine operating data and establishing nonlinear relationships between measured parameters and component faults. Chen Huaguan et al., in "A Review of Gas Turbine Gas Path Fault Diagnosis Technology," noted that current methods primarily employ machine learning algorithms such as support vector machines (SVMs), artificial neural networks (ANNs), deep learning methods, and Kalman filters.

Support vector machines (SVMs) are a novel machine learning method with advantages such as requiring fewer training samples, shorter training times, and high accuracy. Luo Yingfeng et al. found that SVMs achieve satisfactory classification results in gas turbine fault diagnosis, outperforming neural networks when sample sizes are small. Fentaye A.D. et al. combined SVMs with ANNs, demonstrating advantages in complex fault diagnosis. Zhang Yun et al. introduced the gray wolf optimization algorithm into SVMs, improving diagnostic accuracy and speed[7].

Artificial neural networks (ANNs) possess strong feature representation and self-learning capabilities but face challenges such as varying recognition abilities and structural identification difficulties. Zhang Xiao et al. combined the dragonfly algorithm with neural networks, improving diagnostic accuracy and speed. Liu Longbo et al. integrated wavelet transforms with neural networks to achieve accurate gas turbine fault diagnosis[8].

3.2. Thermodynamic Model-Based Diagnostic Methods

Thermodynamic model-based gas path fault diagnosis methods utilize thermodynamic coupling relationships to analyze component health status parameters by calculating gas path parameters. These methods require the establishment of mathematical models based on engine aerothermodynamics, divided into small deviation linearization methods and nonlinear methods. Due to boundary condition disturbances and sensor measurement noise, current research primarily focuses on nonlinear gas path fault diagnosis methods, employing local and global optimization algorithms as driving solvers.

Xu Peng et al. constructed a gas turbine gas path fault model using the small deviation method, deriving correlation equations and simulation results between measured parameter deviations and performance parameter deviations. Jin Yaofei et al. proposed a hybrid model and data-driven fault diagnosis method, which outperformed single-model methods. Yan Binbin combined an improved particle swarm optimization algorithm with a nonlinear model, achieving high accuracy in single-blade fault diagnosis. Later, he integrated SVMs with thermodynamic models, finding that the SVM model based on radial basis kernel functions achieved the highest diagnostic accuracy[9].

3.3. Knowledge-Based Diagnostic Methods

Knowledge-based fault diagnosis methods utilize multi-source fault knowledge and reasoning logic rules to achieve fault diagnosis, including expert systems, fault trees, and rule-based reasoning. This approach features the typical structure of an expert system, enabling full utilization of expert knowledge without requiring precise mathematical models. Gas turbine fault diagnosis knowledge can be acquired through design specifications, by establishing analytical models and summarizing fault case studies to analyze fault mechanisms.

Feng Lanjun et al. developed an expert system for gas turbine fault diagnosis, achieving both precise and imprecise reverse reasoning. Han Xudong proposed a novel gas turbine fault knowledge management system in the context of "smart power plants," developing an intelligent diagnostic system capable of online real-time condition monitoring and fault diagnosis[10].

3.4. Practical Application Cases of Fault Diagnosis Methods

Wu Jian, in Research on Diagnostic Methods and Practical Applications of Gas Turbine Gas Path Faults, proposed a diagnostic model applicable to actual gas path faults in gas turbines and conducted fault diagnosis based on the operational test results of a complete gas turbine. In dynamic process fault diagnosis, taking the test of a three-shaft gas turbine (A) as an example, the turbine triggered a secondary alarm due to the abnormal opening of the low-pressure compressor outlet bleed valve under steady-state conditions. The diagnostic results showed that excluding parameters with significant sensor measurement delays yielded conclusions consistent with the test fault. For steady-state process fault diagnosis, using theoretical values as a baseline often led to deviations, whereas using test data from A as a reference for diagnosing tests B and C produced more reliable results. Additionally, steady-state diagnosis requires converting test data to the same atmospheric conditions.

4. Existing Problems

4.1. Challenges in Marine Turbine Fault Diagnosis

Despite significant advancements in automation and digital technologies for marine turbine fault diagnosis, several issues remain. On one hand, the accuracy and reliability of sensors need further improvement, as sensor failures may lead to inaccurate data, affecting diagnostic precision. On the other hand, while digital technologies can process large volumes of data, deeper data analysis and mining require more advanced algorithms and models to enhance the diagnosis of complex faults. Furthermore, the complexity of marine turbine systems exacerbates compatibility issues among different equipment and systems, impacting the overall performance of automated and digital systems[11].

4.2. Challenges in Gas Turbine Fault Diagnosis

Gas turbine fault diagnosis also faces numerous challenges. Research on fault diagnosis under transient conditions remains relatively insufficient. With increasing demand for peak regulation in power plants, gas turbines must operate more flexibly, making transient condition fault diagnosis critical for ensuring equipment safety. Accurate identification of coupled faults remains difficult due to the growing complexity of gas turbine structures and thermodynamic models, necessitating more precise thermodynamic models and advanced algorithms. Data-driven diagnostic methods are limited when fault samples are scarce or fault feature labels are missing. Thermodynamic model-based methods heavily depend on model accuracy and exhibit low sensitivity to measurement data. Knowledge-based methods struggle with knowledge acquisition and updates, making it difficult to adapt to evolving fault scenarios.

5. Future Prospects

5.1. Development Directions for Marine Turbine Fault Diagnosis Technology

In the future, marine turbine fault diagnosis technology will advance toward greater intelligence, integration, and reliability. Efforts will focus on further improving sensor accuracy and reliability, developing new sensors to enable more comprehensive and precise monitoring of turbine systems. Research and application of data mining and artificial intelligence algorithms will be strengthened to enhance the diagnosis and prediction of complex faults. Integration among marine turbine systems will be promoted to facilitate information sharing and collaborative operations, improving overall diagnostic efficiency and accuracy. Additionally, emphasis will be placed on green and sustainable development, with research into energy-saving, low-emission diagnostic technologies and equipment to reduce the environmental impact of marine operations[12].

5.2. Development Directions for Gas Turbine Fault Diagnosis Technology

Future advancements in gas turbine fault diagnosis will focus on addressing existing challenges to improve diagnostic accuracy and reliability. Research on transient condition fault diagnosis will be intensified, with the development of diagnostic models and algorithms adaptable to transient variations. In-depth studies on coupled fault diagnosis methods will be conducted, establishing more accurate thermodynamic models and combining multiple diagnostic approaches to enhance diagnostic capabilities. Big data, artificial intelligence, and IoT technologies will be leveraged to expand fault sample collection, improve data quality, and refine data-driven diagnostic methods. Continuous optimization of thermodynamic model-based and knowledge-based methods will aim to enhance model precision and knowledge update capabilities. Furthermore, research on fault prediction and health management systems will be strengthened to enable preventive maintenance, reducing repair costs and downtime[13].

6. Conclusion

After decades of development, turbine fault diagnosis technology has evolved from traditional signal processing to an intelligent, data-driven era. Future breakthroughs will be needed in key technologies such as multi-source data fusion and real-time diagnostic algorithm optimization, driving turbine systems toward full lifecycle health management. With the deep integration of artificial intelligence and industrial internet, turbine fault diagnosis will undergo a fundamental shift from passive response to active prediction.

Turbine fault diagnosis technology holds significant importance in marine and industrial applications, having achieved remarkable progress over the years. Marine turbines have realized more efficient fault diagnosis and management through automation and digitalization, while gas turbines have developed diverse diagnostic methods based on data-driven, thermodynamic, and knowledge-based approaches, yielding practical results. However, current turbine fault diagnosis technologies still face challenges, such as insufficient capability in complex conditions, difficulties in diagnosing coupled faults, and limitations in data processing and knowledge updates. Moving forward, with continuous technological advancements, marine and gas turbine fault diagnosis technologies will progress toward greater intelligence, integration, and precision. Through innovation and improvement, these technologies will enhance equipment reliability and safety, providing robust support for the development of marine transportation and industrial production.

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