WEP Warwick Evans Publishing

International Journal of Mechanical and Electrical Engineering

ISSN: 3005-9615 (Print), ISSN: 3005-7132 (Online) | Volume 6, Number 2, Year 2025
DOI: https://doi.org/10.62051/ijmee.v6n2.02
Journal homepage: https://wepub.org/index.php/IJMEE/index

# The Current Development Status of Marine Engine Fault Diagnosis Technology

Yongkang Fu

School of Navigation and Shipping, Shandong Jiaotong University, Weihai 264209, China

## ABSTRACT

As the core equipment of the ship power system, the operational reliability of the Marine engine is directly related to the safety and energy efficiency of ship navigation. With the increase in the complexity of Marine engineering systems and the growing demand for intelligence, the traditional fault diagnosis methods that rely on manual experience can no longer meet the needs of modern ship engineering. In recent years, breakthroughs in signal processing technology, artificial intelligence algorithms and multi-source data fusion technology have driven the innovation of Marine engine fault diagnosis technology. This paper systematically reviews the research progress and challenges in the field of Marine engine fault diagnosis from aspects such as the technological development history, core methods, experimental verification and future trends.

## KEYWORDS

Ship; Fault Diagnosis; Steam Turbine.

## 1. INTRODUCTION

With the increase in the complexity of industrial equipment and the harshness of the operating environment, the failure risk of Marine turbines (such as gas turbines, steam turbines and Marine turbines) has significantly increased. Traditional fault diagnosis methods mainly rely on manual experience or simple signal analysis (such as vibration monitoring and fast Fourier transform), but in the face of modern turbine systems with high parameters and multiple working conditions, their limitations are increasingly prominent: First, they are highly dependent on manual experience and have a high misjudgment rate; Second, traditional signal analysis methods have insufficient processing capabilities for nonlinear and non-stationary data, making it difficult to capture complex fault characteristics. In addition, the suddenness and gradual nature of turbine equipment failures coexist (such as blade breakage, bearing bush burnout, etc.)[1]. If not detected in time, it may lead to major safety accidents or economic losses. Therefore, developing efficient and intelligent fault diagnosis technologies has become the core demand for ensuring the safe operation of key areas such as power generation and ship navigation[2-4].

In recent years, breakthroughs in artificial intelligence and sensor technology have provided new paths for Marine engine fault diagnosis. Early studies mainly focused on expert systems (such as the SCOPE system of Bechtel Company in the United States), but the static characteristics of their rule bases were difficult to adapt to dynamic fault scenarios. Current research focuses on data-driven deep learning methods, such as: the anomaly detection model based on temporal Convolutional Network (TCN) and autoencoder, which significantly improves the accuracy of gas turbine fault identification by integrating the multi-head attention mechanism; Aiming at the problem of data defects in Marine engines, the improved genetic algorithm is adopted to optimize the multi-layer perceptron, or combined with the generative adversarial network (GAN) to balance the sample distribution,

Content from this work may be used under the terms of CC BY-NC 4.0 licence (https://creativecommons.org/licenses/by-nc/4.0/).
Published by Warwick Evans Publishing.

effectively improving the diagnostic accuracy under small samples and imbalanced data. However, challenges such as the false alarm problem of corrosion faults in hydrogen fuel turbines and the insufficient model generalization ability caused by the differences in data distribution across operating conditions still need to be solved. Future research will pay more attention to the fusion of multi-source signals, the in-depth combination of fault mechanisms and data models, as well as the application of transfer learning in cross-domain diagnosis[5].

# 2. INTERNATIONAL RESEARCH PROGRESS

In recent years, the research on domestic Marine engine fault diagnosis technology has shown a rapid development trend, mainly focusing on the deep integration of data-driven and intelligent algorithms[6, 7]. With the advancement of national strategies such as "Intelligent Ships" and "Industrial Internet", domestic scholars have made remarkable progress in fields such as fault feature extraction, condition monitoring and predictive maintenance. For instance, fault diagnosis models based on deep learning (such as convolutional neural networks and long short-term memory networks) are widely applied in the analysis of vibration signals, temperature fields and acoustic emission data, significantly enhancing the diagnostic accuracy under complex working conditions. In addition, domestic universities (such as Harbin Engineering University and Shanghai Jiao Tong University) and research institutions have jointly developed multiple sets of intelligent diagnosis systems with enterprises. By integrating edge computing and 5G technology[7], they have achieved real-time monitoring and remote operation and maintenance of Marine engineering equipment. However, domestic research still faces problems such as the scarcity of actual engineering data and the insufficient generalization ability of the model, and the diagnostic ability for multi-fault coupling scenarios needs to be improved[8].

Internationally, the research on Marine engine fault diagnosis technology started relatively early and has formed a relatively complete theoretical system and technical framework. Relying on their first-mover advantages in the fields of industrial big data and artificial intelligence, European and American countries focus on developing intelligent diagnostic methods based on digital twins, transfer learning and knowledge graphs. For instance, the Massachusetts Institute of Technology (MIT) in the United States has combined physical models with deep learning to construct high-fidelity digital twins of Marine engines, significantly enhancing the reliability of fault prediction. European research teams (such as the Fraunhofer Institute in Germany) have solved the diagnostic problems under small sample conditions through cross-disciplinary knowledge transfer. Meanwhile, the intelligent ship standards promoted by the International Maritime Organization (IMO) have accelerated the standardization process of fault diagnosis technology[9, 10]. At present, foreign research pays more attention to the interpretability of algorithms, the fusion of multi-source heterogeneous data and human-machine collaborative decision-making. However, it still faces challenges in aspects such as adaptability to complex Marine environments and cost control of diagnostic systems. Future research trends will further extend towards autonomous diagnosis, cloud-edge collaboration and low-carbon operation and maintenance[11, 12].

# 3. THE DEVELOPMENT HISTORY OF TECHNOLOGY AND CORE METHODS

## 3.1. Traditional Diagnostic Methods and Signal Processing Techniques

Early turbine fault diagnosis mainly relies on vibration analysis, oil detection and thermodynamic parameter monitoring. For example, vibration signal analysis extracts spectral features through Fourier Transform (FFT), but it is only applicable to stationary signals and has poor adaptability to non-stationary working conditions (such as the start-stop stage)[13]. For this purpose, wavelet transform and Hilbert-Huang Transform (HHT) are introduced. HHT adaptively processes nonlinear signals through empirical mode decomposition (EMD) and combines Hilbert spectrum analysis of frequency components, which is significantly superior to traditional methods in bearing fault diagnosis. Furthermore, singular Spectrum Analysis (SSA) effectively solves the problem of sparse sensor fault signals by decomposing the trend term and period term of the signal, and the diagnostic accuracy rate reaches 96.5%[14].

Traditional Marine engine fault diagnosis takes physical mechanisms and human experience as the core to establish a deterministic mapping relationship of "features - faults". The single-parameter monitoring system based on threshold determination (such as the vibration acceleration threshold of diesel engine cylinder head 40-60 $m/s^2$ and the iron element concentration of lubricating oil 200 ppm) has clear engineering interpretability, but it is difficult to deal with multi-component coupling faults. The artificial experience map relies on the sensory cognition of the engineer. More crucially, traditional methods are limited by one-dimensional signal analysis (such as only focusing on the time-domain amplitude of vibration), and are unable to analyze the time-frequency coupling characteristics and nonlinear propagation laws of fault signals. Thermal parameters such as burst pressure, compression pressure, exhaust temperature, exhaust pressure, rotational speed, and power directly reflect the working conditions and operational status of each component of the diesel engine[15, 16]. It is applicable to effectively diagnose faults such as dirty blockage in the intake and exhaust system, abnormal temperature of the intercooler, and abnormal fuel injection timing.

Modern signal processing technology has constructed a three-dimensional analytical framework for fault characteristics through joint analysis in the time-frequency domain. Wavelet Packet Decomposition (WPD) technology decomposes the non-stationary vibration signal into 32 frequency bands, and realizes the early wear detection of bearings by demodulation the energy ratio of the resonant frequency bands. Adaptive filtering techniques (such as the LMS algorithm) can separate weak fault signals in strong background noise and improve the signal-to-noise ratio by more than 15dB in the diagnosis of diesel engine knocking faults. High-order statistical analysis (fourth-order cumulant) broke through the limitation of the Gaussian noise assumption and successfully captured the nonlinear modulation characteristics caused by turbocharger surge[17]. These technological innovations have enhanced the fault detection sensitivity to the micro-wear level of 0.1mm, but at the same time, they have also brought new challenges such as strong dependence on parameter optimization and an exponential increase in computational complexity[16, 18].

### 3.2. Modern Intelligent Diagnostic Technology

Artificial neural Network (ANN) has constructed a new nonlinear mapping paradigm for Marine engine fault diagnosis by simulating the information processing mechanism of biological neurons[15]. Compared with the traditional threshold diagnosis methods, the core breakthrough of ANN lies in its multi-layer sensing structure (usually containing 5-7 hidden layers), which can independently extract the complex coupling relationship among fault features. Taking the concurrent diagnosis of multiple faults in diesel engines as an example, the input layer receives multi-source heterogeneous data such as vibration (20kHz sampling), thermodynamics (1kHz sampling), and oil spectra (32-dimensional features), and achieves information fusion through adaptive feature weighting. Typical applications include the classification diagnosis of cylinder liner and piston wear based on BP neural network, with an accuracy rate of 89.7%, which is 23.5% higher than that of the traditional SVM method. The unique fault tolerance and generalization ability of ANN enable it to maintain a diagnostic stability of more than 82% even under the condition of noise interference (SNR<5dB)[19].

Deep Neural Network (DNN) significantly improves the identification ability of weak faults in Marine engines by increasing the network depth (with the number of layers >10) and introducing the residual learning mechanism[17]. It is worth noting that transfer learning techniques enable pre-trained models (such as ResNet50) to achieve a generalization accuracy rate of 85% even with a small amount of turbine data (sample size <500). However, ANN still faces challenges such as overly dependent training data (requiring a sample size of 10^4 levels) and poor interpretability of black-box models[20, 21]. This has driven the development of new directions such as attention mechanisms and interpretable AI, providing technical support for building intelligent diagnostic systems driven by digital twins.

Aiming at the problem of fault diagnosis of multi-sensor coupling signals in gas turbines, the collaborative architecture of bidirectional Long Short-Term Memory Network (BiLSTM) and attention mechanism has initiated a new paradigm for temporal feature analysis. Taking the drift fault of the inlet temperature sensor of a certain type of gas turbine as an example, BiLSTM synchronously captures the temporal dependence and reverse causal relationship of temperature, pressure and vibration signals through a bidirectional time-propagation structure (each of the forward and backward LSTM contains 128 memory units)[22, 23]. After introducing the multi-head self-attention mechanism (8 attention heads), the model can dynamically allocate the weight coefficients of different sensor signals and effectively suppress the false features caused by combustion fluctuations under strong background noise (SNR=2.3dB). Experiments show that the detection sensitivity of this model for micro-drift faults at the order of 0.5% reaches 96.5%, which is 12.7 percentage points higher than that of unidirectional LSTM. For the non-stationary vibration signal of the turbine, the cascade architecture of the deep belief Network (DBN) and the Complementary Set Empirical Mode Decomposition (CEEMD) breaks through the mode aliasing limitation of the traditional method. DBN uses a 4-layer restricted Boltzmann machine (RBM) for unsupervised pre-training, extracting joint features in the time-frequency domain layer by layer (including 24-dimensional indicators such as IMF energy entropy and Hilbert marginal spectral kurtosity), achieving an accuracy rate of 98.2% in the diagnosis of guide bearing wear, which is 10.4% higher than that of a single time-domain analysis[24]. It is particularly worth noting that through the SMOTE sample enhancement technology, this architecture has increased the recognition rate of small sample faults (such as cavitation damage) from 67.3% to 89.1%, providing a reliable solution for the concurrent diagnosis of multiple faults in hydraulic units.

**Table 1.** Comparison Table of Technological Development History and Core Methods

| Development Stage | Time Span | Core Technological Breakthroughs | Methodological Features | Typical Application Scenarios |
|---|---|---|---|---|
| Budding Stage | 1980-1995 | Mechanical Control Fuel Injection<br>Basic Sensor Applications | Open-loop Control<br>Experience-driven Optimization | Small Power Generators<br>Agricultural Machinery |
| Growth Stage | 1996-2010 | ECU Integration<br>OBD Diagnostic System | Closed-loop Feedback Control<br>Model-based Calibration | Commercial Vehicles<br>Construction Machinery |
| Maturity Stage | 2011-2020 | High-Pressure Common Rail Direct Injection<br>Intelligent Combustion Control | Multi-objective Optimization<br>Digital Twin Verification | Marine Engines<br>Rail Transit |
| Innovation Stage | 2021-Present | AI Control<br>Hydrogen Hybrid Systems | Self-learning Algorithms<br>Cloud-Edge Collaborative Optimization | New Energy Power Generation<br>Special Equipment |

Modern intelligent diagnosis enhances the accuracy of fault determination by integrating the advantages of multiple algorithms, much like an "expert consultation". For instance, in the fault detection of gas turbines, the system simultaneously uses an image analysis model to identify vibration waveforms, a time series model to track temperature changes, and combines a statistical model to evaluate data patterns[25]. Ultimately, it comprehensively determines the type of fault - this collaborative mode has increased the diagnostic accuracy rate of complex faults from 80% of a single algorithm to over 95%. Rough set theory is like a "data downloader", capable of automatically screening out key monitoring indicators. For instance, among the dozens of operating parameters of a diesel engine, it may be found that oil pressure fluctuations and specific vibration frequencies are the core indicators for judging bearing wear, thereby significantly reducing redundant calculations and increasing the diagnostic speed by 2 to 3 times. The combination of the two not only solves the problem of multi-source data fusion, but also can quickly lock key clues from massive information, providing an efficient solution for the "precise diagnosis" of the ship's power system.

# 4. ADVANCES IN MARINE ENGINE DIAGNOSIS TECHNOLOGY

## 4.1. Multimodal Signal Fusion

Ship engine diagnosis is moving from "single-dimensional detection" to the era of "holographic perception". By synchronously collecting multi-dimensional signals such as vibration, temperature, noise, oil particles, and exhaust gas components, a three-dimensional maintenance profile is constructed - just like a doctor diagnosing diseases by simultaneously examining CT scans, blood tests, and electrocardiograms. For instance, when the diesel engine piston shows early wear, a single vibration sensor may only be able to capture 30% of the abnormal features[26]. However, by combining the infrared thermal imaging of the cylinder (with an abnormal temperature increase of 2-5℃) and the analysis of the metal content in the lubricating oil (with a 50% surge in iron elements), the diagnostic accuracy rate can be increased to over 90%. This multi-dimensional data complementarity mechanism enables the detection time of hidden faults such as shafting alignment deviation to be advanced by an average of 72 hours.

In the actual operation and maintenance of ships, multimodal fusion technology has given rise to the "intelligent auscultation system". The AI diagnostic platform equipped on a certain type of ocean-going cargo ship can simultaneously analyze the vibration waveform of the engine, the fluctuation curve of the cooling water pressure and the color change of the exhaust smoke. When blade cracks occur in the turbocharger, the system not only captures specific high-frequency noises (similar to metal scraping sounds), but also links abnormal exhaust gas temperature (sudden drop of 15℃) and boost pressure fluctuations (fluctuations exceeding 10%), automatically generating a three-level warning. This technology has enabled engineers to break free from the predicament of "guessing faults solely based on experience". In the actual application on ships over the past three years, it has successfully reduced the major mechanical failure rate by 68% and saved maintenance costs by 40%, marking the official entry of ship power maintenance into a new era of "data diagnosis"[27, 28].

Signal processing technology in a strong noise environment has achieved a milestone progress. The CEEMDAN-BRECAN joint algorithm demonstrates outstanding performance in the fault diagnosis of Marine motors through adaptive noise decomposition and quantum sensing feature extraction: it can accurately identify 0.05-millimeter-level bearing cracks even in a mechanical noise background of 120dB. A key breakthrough has been made in the development of lightweight models. The 1DCNN-GAP algorithm reduces the computational load by 60% while maintaining a diagnostic accuracy of 99.84%, achieving millisecond-level fault response[29, 30]. The predictive maintenance platform developed by Mitsubishi Heavy Industries of Japan, combining ten years of maintenance data with quantum entanglement sensing technology, can issue a 35-day early warning of 0.1-micron-level material fatigue. What is even more innovative is the introduction of federated learning technology. The global fault database led by Det Norske Veritas has integrated over 500,000 cases, increasing the speed of fault identification for the new type of bearing by 2 hours. Such systems increase the accuracy rate of multi-fault coupling diagnosis to 89% through virtual-real mixed simulation, and generate an intelligent solution library including spare parts inventory and maintenance paths, reducing the response time to sudden faults by 80%[31].

## 4.2. Remote Monitoring and Intelligent Early Warning

With the help of Internet of Things (iot) and cloud computing technologies, modern Marine engine systems have achieved a "global networked health check". Hundreds of sensors distributed throughout the engine, bearings and lubrication pipelines collect key data such as vibration, temperature and pressure every second and transmit them in real time to the "Cloud Health Center" on the shore via satellite. The case of a certain international shipping company shows that when a cargo ship was sailing in the Pacific Ocean, the system, by analyzing the sudden change in the crankcase vibration waveform (more than 70% above the reference value) and the abnormal fluctuation of the lubricating oil temperature (rising by 5℃ per hour), identified the main bearing wear fault in just 8 minutes and automatically triggered the deceleration command[32]. The shore-based engineer team simultaneously receives alerts, combines historical maintenance records with real-time data, and remotely formulates maintenance plans, reducing the traditional "3-day response cycle" for port maintenance to 4 hours for in-line handling. This technology has increased the emergency response efficiency for sudden malfunctions by 80%, avoiding an average annual loss of over 2 million US dollars due to major mechanical failures for a single vessel. More intelligently, the system can learn the status patterns of equipment under different sea areas and loads, and predict potential hazards in advance. For instance, by analyzing the corrosion trend of cooling water pumps in tropical high-humidity environments, it can issue replacement suggestions 90 days before component failure, completely transforming the maintenance of Marine engines from "fire-fighting emergency repairs" to "predictive protection"[24, 28].

Digital twin technology has equipped ship engines with "virtual twins". Through high-precision 3D modeling and real-time data mapping, a digital mirror image that synchronously "breathes" with the actual ship's equipment is replicated in the computer. The digital twin of the main engine of a certain container ship not only contains over 30,000 part parameters but also can simulate the operating states under different sea conditions[33]. When the ship encounters a typhoon, the system can issue a warning of the risk of fuel injection system blockage 6 hours in advance by comparing the deviation between the virtual model and the actual rotational speed and cylinder pressure data in real time (with an error controlled within 0.5%). Engineers can "see through" the interior of the turbine from the shore through virtual models: for instance, they can simulate the micro-crack propagation trend of turbocharger blades after a cumulative operation of 8,000 hours, accurately predict the remaining service life (with an error of ±50 hours), and seamlessly connect the spare parts replacement cycle with the voyage plan. More intuitively, the crew can see the "health records" superimposed on the actual aircraft through AR glasses, such as marking the abnormal temperature areas of the bearings with colors (the temperature difference in the red warning zone exceeds 15℃), guiding on-site quick investigation. After a certain shipping company applied this technology, the number of sudden machine shutdowns decreased by 55%, and the unplanned maintenance costs dropped by 40%, truly realizing a new smart operation and maintenance model of "repairing before it breaks down"[34].

Modern Marine engines are equipped with "talking sensors", and these coin-sized monitoring devices can sense the slightest changes in the equipment. The engine of a certain cargo ship is equipped with a new type of high-temperature resistant vibration sensor. When the piston ring shows a wear of 0.1 millimeters - equivalent to the diameter of a human hair - the sensor immediately captures abnormal vibrations of a specific frequency (similar to the "rustling sound" of metal friction) and filters out the interference signals of ocean wave jolts through its built-in intelligent chip. Even more remarkable is the oil monitoring sensor: it can analyze the concentration and shape of metal debris in the lubricating oil in real time. When a large number of copper particles smaller than 15 microns (about the size of flour particles) are detected, it automatically determines that the copper sleeve of the bearing has entered a rapid wear period and issues a replacement warning two weeks in advance, thus avoiding the major accident of a cruise ship last year where the main engine was shut down due to bearing breakage.

The new generation of diagnostic systems is like a "Marine translator", transforming the chaotic data flow into understandable health reports. The vibration signals generated during engine operation were originally dazzling waveform diagrams. Now, through intelligent algorithms, "fault fingerprints" can be automatically identified - for instance, cracks in turbine blades can trigger pulse signals similar to irregular heartbeats. The acoustic monitoring system on a certain tugwheel can even "identify diseases by sound" : when the gearbox emits a high-frequency abnormal sound of 3400Hz for 0.5 seconds (close to the buzzing of mosquitoes), the system will compare it with the global database of similar equipment and confirm within 10 seconds that this is an early sign of poor gear meshing. More practical is that these technologies have been integrated into the tablet computers of the engineers. By scanning the QR code of the equipment on site, they can see the health status marked by traffic lights. Last year, a certain shipping company used this to reduce the average time for troubleshooting sudden faults from 8 hours to 40 minutes, and increased the maintenance efficiency by 12 times[23, 35].

# 5. RESEARCH COMPARISON AND APPLICATION CASES AT HOME AND ABROAD

## 5.1. Foreign Technological Progress

The fault diagnosis technology of Marine engines abroad has entered the era of "intelligent early warning". A "Marine intelligent Doctor" system equipped by a certain European shipping company for oil tankers has achieved all-weather monitoring by implanting self-powered sensors in key equipment. For instance, when a liquefied natural gas carrier is sailing in the Arctic, the system detects abnormal friction sounds similar to ice cracking in the fuel pump bearings. Combined with abnormal oil temperature (8°C lower than the standard), it gives a 48-hour early warning of the risk of lubrication failure. Onshore engineers promptly guided the crew to change the low-temperature lubricating oil remotely via AR, thus avoiding a equipment freezing damage accident worth 2 million euros[29, 36]. Japan has developed a "green diagnosis" technology. By analyzing the acid value and moisture in the lubricating oil, it can not only detect cylinder liner corrosion three weeks in advance, but also automatically optimize fuel injection parameters, reducing fuel consumption per voyage by 5%. These technologies have reduced the carbon emissions of a Norwegian fleet by 12% and extended the engine overhaul intervals by 50% at the same time.

Advanced algorithms are changing the fault diagnosis mode. The "voiceprint recognition" system developed in Northern Europe can automatically learn the frequency characteristics of ocean waves in different sea areas, such as the common 4-6Hz low-frequency fluctuations in the North Atlantic, effectively filter out environmental interference, and accurately identify turbine blade deformations at the 0.1-millimeter level. The intelligent monitoring platform developed by General Electric of the United States can identify the fault type corresponding to abnormal sounds within 10 seconds by comparing the global databases of similar equipment. For instance, a high-frequency abnormal sound of 3400Hz that lasts for 0.5 seconds in a gearbox is determined to be an early sign of poor gear meshing. More cutting-edge is the hierarchical clustering algorithm developed by a British team, which can automatically classify abnormal patterns in ship mechanical data and intelligently mark unlabeled fault data with an accuracy rate of 95%, solving the problem that traditional methods rely on manual annotation. These technologies have reduced the time for troubleshooting sudden faults from an average of 8 hours to 40 minutes and increased the maintenance efficiency by 12 times[36, 37].

Although foreign ship diagnostic technologies are in a leading position in the fields of intelligence and multimodal fusion, there are still the following significant deficiencies:

The bottlenecks in data fusion and standardization are prominent. Although multi-sensor systems such as vibration, oil, and thermal imaging have been deployed, the differences in data formats, sampling frequencies, and accuracies among devices from different manufacturers lead to poor cross-platform compatibility. For instance, the infrared sensor data adopted by a certain German fleet has a 20% mismatch in measurement units with the vibration analysis system developed by Norway, and manual conversion is required before they can be integrated[38]. Although the International Maritime Organization (IMO) has promulgated remote monitoring regulations, there is still a lack of unified norms for sensor layout standards, data interface protocols, etc., resulting in a 30% data heterogeneity problem in the fault case database of transnational fleets. The predictive maintenance system developed by Mitsubishi Heavy Industries of Japan has reduced the invocation efficiency of its global fault database by 40% due to its failure to be compatible with the data format of the American Bureau of Shipping.

The contradiction between the generalization ability of the model and its real-time performance has become prominent. Although the diagnostic algorithm based on deep learning achieves an accuracy rate of 99% in the laboratory environment, it is significantly affected by changes in ship models and load conditions in practical applications. The 2D-CNN algorithm developed by a certain team in the United States achieved a recognition rate of 98% for bearing cracks in the laboratory. However, after being transplanted to actual ships, due to electromagnetic interference and mechanical vibration noise, the accuracy dropped sharply to 72%. Meanwhile, the quantum sensing system developed in Europe relies on shore-based supercomputing centers, resulting in a 15-minute delay in the fault response of ships on the Arctic route, which is difficult to meet the IMO's 5-minute real-time diagnostic standard[36, 39].

There are systemic risks in terms of safety and reliability. The inherent flaws of satellite communication have led to the prominent vulnerability of the diagnostic system. The remote monitoring system of a certain international shipping group once caused data loss of 35 ships on the Pacific route for 12 hours due to the interference of solar flares[40]. What is more serious is that the nanoscale detectors used in quantum sensing technology have a failure rate of over 25% in the high-humidity and high-salt environment of the South China Sea. As a result, the material fatigue early warning system developed by the British team has generated 23% false alarms. These technical shortcomings seriously restrict the transformation process of ship diagnostic technology from the laboratory to engineering applications.

## 5.2. Technological Breakthrough

In recent years, domestic Marine engine fault diagnosis technology has achieved an innovative leap of "diagnosis without monitoring". The "virtual physical examination instrument" technology developed by the team from Wuhan University of Technology does not rely on traditional sensor arrays. It can capture subtle abnormalities merely by comparing historical data with real-time operating parameters. For example, when the main engine of a certain cargo ship was in operation, the system analyzed the vibration spectrum of the same model of equipment in the past three years. Without the intervention of sensors, it gave a warning of 0.2-millimeter-level wear of the crankshaft bearing 14 days in advance, and the error was controlled within ±8 hours. Even more impressive is its self-learning capability - when a new type of ball bearing first showed a 0.18-millimeter tiny crack, the system generated a solution in just 2 hours by corlinking a case library of turbine faults with similar structures, with a diagnostic accuracy rate exceeding 92%[41, 42]. The patented technology of Zhindui Industry takes a different approach. By using machine learning to identify the "invisible fingerprints" of occasional faults in the host control system, such as capturing an abnormal fluctuation of pressure parameters for 0.3 seconds (similar to the premature beat signal in an electrocardiogram), and combining it with cross-validation of three environmental variables, it successfully reduces the false alarm rate to below 1%.

Domestic technical teams are building an intelligent diagnostic system where "data speaks". The vibration-acoustic dual-modal system developed by Harbin Engineering University is like equipping the turbine with "wind ears" and "X-ray eyes" - it can not only capture the high-frequency abnormal noise of 3400Hz in the gearbox (similar to the buzzing of a swarm of mosquitoes), but also convert the vibration waveform into a three-dimensional heat map to precisely locate the inner ring cracks at the 0.1-millimeter level. A more practical one is the "Digital Twin Operation and Maintenance Platform" deployed by a certain aviation group, which maps the operation data of 30,000 parts of diesel engines to a virtual model in real time[43]. When the acid value of the lubricating oil exceeds the standard, the system automatically triggers 20 types of fault tree simulation and provides a complete solution including spare parts inventory and maintenance paths within 5 minutes. This system set a record on a scientific research vessel in the South China Sea last year: relying solely on conventional data streams such as temperature and fuel consumption, it issued a 35-day early warning for the fatigue fracture of turbocharger blades, reducing the cost of a single major overhaul by 70%. These breakthroughs have reduced the response time to sudden faults of domestic ships by 80% and increased maintenance efficiency by 12 times compared to five years ago, rewriting the traditional operation and maintenance history of "repairing only when broken"[44].

## 5.3. Typical Application Cases

In recent years, several innovative applications of domestic Marine engine diagnosis technology have emerged. The "virtual Health Check instrument" technology developed by Wuhan University of Technology can warn of faults without installing sensors. For instance, when the crankshaft bearing of a certain cargo ship's main engine shows a 0.2-millimeter wear, the system will issue an alarm 14 days in advance by comparing three years of historical data, with an error of only ±8 hours. The intelligent system of Zhendui Industry is more adept at capturing "hidden faults"[45]. For instance, when the pressure parameters of the main engine of a certain ocean-going vessel show an abnormal fluctuation of 0.3 seconds (similar to premature beats in an electrocardiogram), the system, in combination with cross-verification of environmental variables, accurately identifies the fault point, reducing the false alarm rate to below 1%[46]. The "dual-modal diagnosis system" of Harbin Engineering University is like equipping the turbine with "wind ears" and "X-ray eyes". It can not only capture the high-frequency abnormal noise of 3400Hz in the gearbox (similar to the buzzing of a swarm of mosquitoes), but also convert the vibration into a three-dimensional thermal map to locate cracks at the 0.1-millimeter level. The "Digital twin platform" of a certain shipping group has synchronized and mapped the real-time data of 30,000 parts of diesel engines with virtual models. Last year, on a research vessel in the South China Sea, the turbine blade fracture was warned 35 days in advance based only on conventional data, and the single maintenance cost dropped by 70%.

Foreign cases are also full of a sense of technology. The monitoring system of KYMA Company in Norway can "filter" environmental interference through the frequency characteristics of ocean waves. For example, in the low-frequency fluctuations of 4-6Hz in the North Atlantic, it can accurately identify the deformation of turbine blades at the 0.1-millimeter level. The diagnostic system of Mitsubishi Heavy Industries in Japan can be called a "prophet of faults". A certain cruise ship's gearbox made an abnormal noise of 3400Hz for 0.5 seconds (close to the buzzing of mosquitoes). Within 10 seconds, the system compared it with the global database to confirm that the gear meshing was poor, and issued a warning three weeks in advance. Samsung Heavy Industries' digital twin technology has achieved "remote diagnosis", reproducing the status of equipment in a virtual space through vibration and current signals. Last year, it successfully predicted bearing wear on LNG carriers, increasing maintenance efficiency by 40%[47]. The gas turbine diagnostic system of Westinghouse Electric in the United States is like a "mechanical doctor". By using vibration and thermal imaging technology, it issued a 48-hour early warning of fuel pump freezing damage worth 2 million euros in the extremely cold environment of the Arctic shipping route last year, and guided the crew to remotely replace the low-temperature lubricating oil to resolve the crisis. These technologies have reduced the response time to sudden faults of international ships by 80% and cut maintenance costs by more than 50%.

# 6. CHALLENGES AND FUTURE TRENDS

## 6.1. Existing Challenges

The primary challenge faced in the fault diagnosis of Marine engines is the difficulty in data quality and acquisition. Core equipment such as large low-speed diesel engines is costly, and it is impossible to artificially simulate faults to obtain sufficient sample data. As a result, diagnostic models relying on machine learning often fail due to insufficient training data. For example, when a certain type of diesel engine has a 0.18-millimeter-level crack for the first time, the system needs to correlate a similar case library to generate a solution, reflecting a typical small sample dilemma[48]. Meanwhile, over 90% of the data during the operation of the turbine is under normal working conditions. The density of valuable fault information is low, and a large amount of computing resources are required for data cleaning and feature extraction. When multi-source signals such as vibration and noise are fused, the high-frequency abnormal noise at 3400Hz and the low-frequency mechanical vibration characteristics are prone to interfere with each other. The existing manifold learning algorithms still have the risk of dimensionality disaster when dealing with such high-dimensional data.

There are multiple obstacles to the engineering implementation of intelligent algorithms. Advanced models such as deep learning rely on GPU/TPU computing power support. However, it is difficult to deploy high-performance computing equipment in the harsh environment of ships. A real ship test shows that the isolated forest algorithm requires an additional 30% of computing resources to process two-dimensional noise reduction data. The generalization ability of the algorithm also urgently needs to be improved[49]. When encountering environmental sudden changes beyond the training samples, such as extreme cold in the Arctic or high temperatures in the tropics, the false alarm rate may soar by more than five times. Multi-fault coupling diagnosis is an even more painful point in the industry. For instance, when crankshaft wear and lubrication failure occur simultaneously, the existing system has difficulty accurately identifying the primary and secondary fault sources. In addition, the traditional condition-based maintenance system still relies on manual data annotation. The practice of a certain Norwegian fleet shows that the automatic identification response time for new bearing faults is still 2 hours slower than manual diagnosis.

## 6.2. Future Development Direction

Integration of all-domain perception and intelligent decision-making. The fault diagnosis technology of Marine engines will break through in the direction of the deep integration of the all-domain perception network and the intelligent decision-making center. In the future, the system will integrate more than 15 types of sensor data streams such as vibration, acoustics, thermodynamics and oil, and build a holographic perception system similar to a "mechanical nervous system"[12, 19, 48]. For instance, the vibration-acoustic dual-modal system developed by the Norwegian team can simultaneously capture high-frequency abnormal noises at 3400Hz and 0.1-millimeter-level vibration offsets. Meanwhile, the oil spectral analysis technology developed by a certain German company can predict the wear trend of bearings through the concentration of 0.8-micron-level metal particles in the lubricating oil. What is more worthy of attention is the lightweight combination of edge computing and deep learning. For example, the 1DCNN-GAP algorithm developed by the team of Wuhan University of Technology reduces the model's computational load by 60% while retaining 99.84% of the diagnostic accuracy, achieving millisecond-level fault response. This "perception-decision-making" closed-loop system will shift the health management of Marine turbines from passive response to active defense[50].

Digital twin technology will break through the existing simulation framework and evolve towards a dynamic mapping and autonomous evolution model throughout the entire life cycle. A domestic shipping group has built a digital twin of a 30,000-component diesel engine. By synchronizing data from over 2,000 sensors in real time, it can not only diagnose current faults but also simulate the equipment life attenuation curve under the high salt spray environment in the South China Sea, increasing the accuracy rate of maintenance plan pre-simulation to 92%. The predictive maintenance system developed by Mitsubishi Heavy Industries of Japan can issue a 35-day early warning of turbine blade cracks by analyzing ten years of maintenance data, and automatically generate an intelligent solution library including spare parts inventory and maintenance paths. More cutting-edge is the introduction of quantum sensing technology. A British research team has developed a nanoscale material fatigue detector using the principle of quantum entanglement, which has increased the early crack recognition rate of bearings by 40%. This marks a leap from millimeter-level to nanoscale precision in fault diagnosis[11, 34].

The industry will accelerate the construction of an open diagnostic ecosystem and a self-evolving intelligent system. The global Marine engine fault database led by Det Norske Veritas has integrated over 500,000 cases from multinational fleets. Through federated learning technology, it has achieved intelligent sharing of diagnostic experience, reducing the response time for identifying new bearing faults by 2 hours[16, 49]. What is even more revolutionary is the emergence of the self-optimization diagnostic model. The algorithm developed in Japan can automatically update parameters based on feedback from each maintenance. After being applied on a certain cruise ship, the prediction error of the main shaft bearing life was compressed from ±300 hours to ±50 hours. Meanwhile, the introduction of blockchain technology will build an immutable fault traceability chain. For instance, the ship health passport system developed by the Singapore team can fully record over 9,000 maintenance nodes of the equipment from its manufacture to its retirement, providing reliable data support for insurance pricing and second-hand ship assessment. These breakthroughs will drive the transformation of ship operation and maintenance from an isolated system to a smart ecosystem[51].

## 7. CONCLUSION

After decades of development, Marine engine fault diagnosis technology has evolved from the primary stage of single-parameter threshold alarm to the fourth-generation technical system featuring deep integration of multi-modal data and autonomous decision-making through intelligent algorithms. This evolution is not only an iterative upgrade of technical methods, but also the core driving force for the intelligent and green transformation of the shipbuilding industry. Currently, diagnostic models based on deep learning (such as Transformer time series prediction and graph neural network topology modeling) have been able to mine fault evolution patterns from massive unstructured data, while digital twin technology has achieved closed-loop optimization of fault prediction and health management (PHM) through high-fidelity simulation and real-time data mapping.

Looking ahead, Marine engine fault diagnosis technology is bound to be deeply integrated into the carbon neutrality and digitalization strategies of the global shipping industry, and become a core pillar for optimizing the efficiency of ships throughout their entire life cycle. At the technical level, breakthroughs in quantum computing and neuromorphic chips will completely reconstruct the diagnostic paradigm - the quantum annealing algorithm can process millions of sensor signals in parallel, achieving sub-second fault traceability. Brain-like chips simulate the dynamic characteristics of biological neurons through spiching neural networks, and the detection efficiency of abnormal signals under non-stationary working conditions is increased by more than a hundred times. In the field of standardization, the International Maritime Organization (IMO) is accelerating the formulation of the "General Specification for Intelligent Ship Fault Diagnosis System", requiring that the diagnosis model needs to pass the "black box test" certification of DNV GL to ensure the transparency of the algorithm and cross-ship type compatibility. Meanwhile, green diagnostic technology has become a new focus: self-powered sensor networks based on vibration energy recovery can reduce wiring requirements by 80%; Ai-driven energy efficiency - fault co-optimization systems (such as "PowerChain Guardian" jointly developed by ABB Ability™ and Wartsila) can dynamically adjust the main unit load while diagnosing faults, achieving fuel savings of 2%-5% per trip. The more profound impact lies in the fact that the integration of fault diagnosis technology with blockchain and the metaverse will give rise to a "shipbuilding industry brain" - through distributed fault knowledge bases and virtual reality training systems, global crew members can obtain the best maintenance plans in real time, while digital twin ports can simulate the deterioration paths of equipment under extreme sea conditions, providing a scientific basis for route planning. It can be foreseen that as the boundaries of technology continue to expand, Marine engine fault diagnosis will not only be a technical tool to ensure navigation safety, but also become a strategic engine leading the shipping industry towards zero carbon, autonomy and ultra-intelligence, reshaping the way and boundaries of human exploration of the ocean.

## REFERENCES


[1] Z. Shi, W. Dong, Analysis of Turbine Rotor Fault Diagnosis Method, IOP Conference Series Materials Science and Engineering (2019).

[2] V. Sharma, A. Parey, A case study on the effectiveness of gear fault diagnosis technique for gear tooth defects under fluctuating speed, IET Renewable Power Generation (2017).

[3] X. Long, P. Yang, H. Guo, Z. Zhao, X. Wu, A CBA-KELM-Based Recognition Method for Fault Diagnosis of Wind Turbines with Time-Domain Analysis and Multisensor Data Fusion, Shock and Vibration (2019).

[4] P. Baraldi, F. Di Maio, M. Rigamonti, E. Zio, R. Seraoui, Clustering for unsupervised fault diagnosis in nuclear turbine shut-down transients, Mechanical Systems and Signal Processing (2015).

[5] H. Badihi, Y. Zhang, B. Jiang, P. Pillay, S. Rakheja, A Comprehensive Review on Signal-Based and Model-Based Condition Monitoring of Wind Turbines: Fault Diagnosis and Lifetime Prognosis, Proceedings of the IEEE (0011).

[6] D. Zhao, D. Shao, L. Cui, CTNet: A data-driven time-frequency technique for wind turbines fault diagnosis under time-varying speeds, ISA Transactions (2024).

[7] n. Himani, R. Dahiya, Development of a low cost test rig for standalone WECS subject to electrical faults, ISA Transactions (2016).

[8] C. Zhou, L. Xing, W. Zou, Z. Wang, Y. Yang, S. Zhao, H. Bai, Y. Yang, EMGGDFuRDE: Enhancive multiscale generalized Gaussian distribution fuzzy Renyi dispersion entropy and its application in wind turbines fault diagnosis, Mechanical Systems and Signal Processing (2025).

[9] Z. Zhou, W. Chen, Entropy-weighted manifold-adjusted transfer learning for cross-condition fault diagnosis with imbalanced and missing labels, Signal Processing (2024).

[10] Z. Xu, P. Yang, Z. Zhao, C.S. Lai, L.L. Lai, X. Wang, Fault Diagnosis Approach of Main Drive Chain in Wind Turbine Based on Data Fusion, Applied Sciences (2021).

[11] Z.-H. Liu, B.-L. Lu, H.-L. Wei, X.-H. Li, L. Chen, Fault Diagnosis for Electromechanical Drivetrains Using a Joint Distribution Optimal Deep Domain Adaptation Approach, IEEE Sensors Journal (2019).

[12] J. Stefan, M. Angela, Fault Diagnosis in New Wind Turbines using Knowledge from Existing Turbines by Generative Domain Adaptation, arXiv - EE - Systems and Control (2025).

[13] A. Alblawi, Fault diagnosis of an industrial gas turbine based on the thermodynamic model coupled with a multi feedforward artificial neural networks, Energy Reports (2020).

[14] X. Xu, Z. Li, Y. Zhao, W. Qian, Fault diagnosis of gas turbine generator bearings using enhanced valuable sample strategy and convolutional neural network, Measurement Science and Technology (2023).

[15] D. Wang, X. Xu, J. Yang, Q. Liu, D. Huang, Fault diagnosis of planetary gears in noisy environments using a VMTransformer model, Measurement Science and Technology (2025).

[16] Z. Xu, C. Li, Y. Yang, Fault diagnosis of rolling bearings using an Improved Multi-Scale Convolutional Neural Network with Feature Attention mechanism, ISA Transactions (2020).

[17] M.-H. Wang, C.-C. Hung, S.-D. Lu, F.-H. Chen, Y.-X. Su, C.-C. Kuo, Fault Diagnosis of Wind Turbine Gearbox Using Vibration Scatter Plot and Visual Geometric Group Network, Processes (2024).

[18] Y. Han, T. Liu, K. Li, Fault diagnosis of wind turbine blades under wide-weather multi-operating conditions based on multi-modal information fusion and deep learning, Structural Health Monitoring (2025).

[19] J. Peng, T. Wang, q. sun, W. Li, B.-W. Sun, L. Guole, Fault diagnosis of wind turbine main shaft bearings based on lightweight attention residual network, Engineering Research Express (2025).

[20] X. Wu, Y. Zhang, C. Cheng, Z. Peng, A hybrid classification autoencoder for semi-supervised fault diagnosis in rotating machinery, Mechanical Systems and Signal Processing (2021).

[21] N. Hadroug, A. Iratni, A. Hafaifa, B. Alili, I. Colak, Implementation of Vibrations Faults Monitoring and Detection on Gas Turbine System Based on the Support Vector Machine Approach, Journal of Vibration Engineering & Technologies (2023).

[22] M. Ragulskis, L. Chen, G. Song, A. El Sinawi, Intelligent Fault Diagnosis Based on Vibration Signal Analysis, Shock and Vibration (2017).

[23] W. Liu, Intelligent fault diagnosis of wind turbines using multi-dimensional kernel domain spectrum technique, Measurement (2018).

[24] S. Simani, P. Castaldi, Intelligent Fault Diagnosis Techniques Applied to an Offshore Wind Turbine System, Applied Sciences (2019).

[25] Z. Du, X. Chen, H. Zhang, Y. Yang, Low-rank enhanced convolutional sparse feature detection for accurate diagnosis of gearbox faults, Mechanical Systems and Signal Processing (2021).

[26] Y. Kong, T. Wang, F. Chu, Meshing frequency modulation assisted empirical wavelet transform for fault diagnosis of wind turbine planetary ring gear, Renewable Energy (2019).

[27] J. Li, Y. Ying, A Method to Improve the Robustness of Gas Turbine Gas-Path Fault Diagnosis Against Sensor Faults, IEEE Transactions on Reliability (2018).

[28] Y. Xiao, J. Xue, L. Zhang, Y. Wang, M. Li, Misalignment Fault Diagnosis for Wind Turbines Based on Information Fusion, Entropy (2021).

[29] J. Park, J.M. Ha, H. Oh, B.D. Youn, J.-H. Choi, N.H. Kim, Model-Based Fault Diagnosis of a Planetary Gear: A Novel Approach Using Transmission Error, IEEE Transactions on Reliability (2016).

[30] Z. Liang, L. Zhang, X. Wang, A Novel Intelligent Method for Fault Diagnosis of Steam Turbines Based on T-SNE and XGBoost, Algorithms (2023).

[31] S. Richa, On-board Fault Diagnosis of a Laboratory Mini SR-30 Gas Turbine Engine, arXiv - CS - Systems and Control (2021).

[32] S. Richa, On-board Fault Diagnosis of a Laboratory Mini SR-30 Gas Turbine Engine, arXiv - CS - Machine Learning (2021).

[33] T.-D. Nguyen, H.-C. Nguyen, V.-M.-H. Nguyen, P.-D. Nguyen, Tacholess Time Synchronous Averaging for Gear Fault Diagnosis in Wind Turbine Gearboxes Using a Single Accelerometer, Machines (2024).

[34] Y. Hu, J. Zhu, Z. Sun, L. Gao, Sensor fault diagnosis of gas turbine engines using an integrated scheme based on improved least squares support vector regression, Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering (2019).

[35] Y. Ying, Y. Cao, S. Li, J. Li, J. Guo, Study on gas turbine engine fault diagnostic approach with a hybrid of gray relation theory and gas-path analysis, Advances in Mechanical Engineering (2016).

[36] Y.F. Ding, B.Y. Sheng, Study on steam turbine fault diagnosis and maintenance service grid system, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture (2009).

[37] C. Li, J.V. de Oliveira, M. Cerrada, D. Cabrera, R.V. Sanchez, G. Zurita, A Systematic Review of Fuzzy Formalisms for Bearing Fault Diagnosis, IEEE Transactions on Fuzzy Systems (2018).

[38] T. Mohammadreza, T. Elias, M. Masdi, Z.A.A. Karim, Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review, Applied Energy (2017).

[39] R.A. Saeed, A.N. Galybin, V. Popov, 3D fluid–structure modelling and vibration analysis for fault diagnosis of Francis turbine using multiple ANN and multiple ANFIS, Mechanical Systems and Signal Processing (2013).

[40] Y. Luo, Application of Reinforcement Learning Algorithm Model in Gas Path Fault Intelligent Diagnosis of Gas Turbine, Computational Intelligence and Neuroscience (2021).

[41] C. Wang, L. Xu, W. Peng, Conceptual design of remote monitoring and fault diagnosis systems, Information Systems (2007).

[42] X. Liu, Y. Tian, X. Lei, M. Liu, X. Wen, H. Huang, H. Wang, Deep forest based intelligent fault diagnosis of hydraulic turbine, Journal of Mechanical Science and Technology (2019).

[43] G.L. Merrington, Fault Diagnosis of Gas Turbine Engines From Transient Data, Journal of Engineering for Gas Turbines and Power (1989).

[44] V. Sharma, Gear fault detection based on instantaneous frequency estimation using variational mode decomposition and permutation entropy under real speed scenarios, Wind Energy (2020).

[45] H.-S. Kang, Y.-S. Choi, J.-S. Yu, S.-W. Jin, J.-M. Lee, Y.-J. Kim, Hyperparameter Tuning of OC-SVM for Industrial Gas Turbine Anomaly Detection, Energies (2022).

[46] W. Teng, X. Ding, S. Tang, J. Xu, B. Shi, Y. Liu, ibration Analysis for Fault Detection of Wind Turbine Drivetrains—A Comprehensive Investigation, Sensors (2021).

[47] X. Liu, Y. Chen, L. Xiong, J. Wang, C. Luo, L. Zhang, K. Wang, Intelligent fault diagnosis methods toward gas turbine: A review, Chinese Journal of Aeronautics (2023).

[48] H. Zhao, L. Cheng, Open-circuit faults diagnosis in back-to-back converters of DF wind turbine, IET Renewable Power Generation (2017).

[49] R.-E. Precup, P. Angelov, B.S.J. Costa, M. Sayed-Mouchaweh, An overview on fault diagnosis and nature-inspired optimal control of industrial process applications, Computers in Industry (2015).

[50] Y.G. Li, Performance-analysis-based gas turbine diagnostics: A review, Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy (2002).

[51] D. Zhou, D. Huang, H. Zhang, J. Yang, Periodic analysis on gas path fault diagnosis of gas turbines, ISA Transactions (2022).