Sustainable Development
ISSN Print: 3104-4174
ISSN Online: 3104-4182
CD ISSN: 3104-4190
https://doi.org/10.63313/SD.2002

Intelligent Fault Diagnosis Technology for Mechanical Equipment: Current Status and Development

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How to cite this paper: Li, G. D., & Yang, F. Z. (2025). Intelligent Fault Diagnosis Technology for Mechanical Equipment: Current Status and Development. Sustainable Development, 1(1), 40-50. ISSN Print: 3104-4174; ISSN Online: 3104-4182.
https://doi.org/10.63313/SD.2002
Published: 2025-10-17

Abstract

With the continuous advancement of technology, mechanization is also progressing, and automated and intelligent technologies are being increasingly developed. Machinery and equipment are exerting a growing influence in modern industrial technology. However, due to their complexity, malfunctions during operation can disrupt the entire operational system. Such disruptions can lead to significant economic losses and potentially cause injuries or fatalities in mechanical engineering or construction projects. Therefore, intelligent fault diagnosis of mechanical equipment is crucial. It not only ensures the normal operation of machinery but also enhances efficiency throughout the system, thereby fostering the development of industrial production.

Keywords

mechanical equipment; fault diagnosis technology; current status and development

Introduction

We are situated in an industrial era profoundly driven by technology, where leaps in productivity are deeply rooted in advancements in science and technology. With the widespread adoption and application of modern mechanical equipment across various industries, the levels of automation and intelligence continue to rise, while internal components become increasingly precise and complex. This transformation has largely replaced traditional manual labor with mechanized production, significantly enhancing not only production efficiency and product consistency but also establishing it as a core engine for economic growth. Consequently, societal reliance on and preference for mechanized equipment are intensifying, and its scope of application is continuously expanding [1-3].

However, failures during the long-term, high-intensity operation of mechanical equipment are almost inevitable. Due to a series of physical and chemical processes such as fatigue, wear, corrosion, and material aging, critical components like bearings, gears, and transmission shafts are prone to issues including cracks, deformation, connection fractures, and even loosening or loss of screws. If these potential hazards are not detected and accurately diagnosed in a timely manner, minor component failures can escalate into unplanned shutdowns of entire production lines. This, in turn, can lead to substantial direct and indirect economic losses. In high-risk and high-reliability sectors such as aerospace, energy and chemical industries, and high-speed rail transportation, the consequences of mechanical failures are even more severe, potentially triggering catastrophic equipment accidents and personnel casualties. Such incidents not only severely disrupt normal production schedules but also cause irreparable damage to a company's market reputation and public image.

Against this backdrop, intelligent fault diagnosis technology for mechanical equipment has emerged and is gradually becoming the cornerstone for ensuring the safety, stability, and efficient operation of modern industry. This technology aims to integrate sensor technology, signal processing, artificial intelligence algorithms, and big data analytics to achieve real-time monitoring of equipment operational status, early extraction of fault features, and intelligent identification of fault types. Thereby, it facilitates a shift from traditional "reactive maintenance" and "periodic maintenance" models towards a proactive "predictive maintenance" paradigm. This paper will focus on intelligent fault diagnosis technology for mechanical equipment, systematically reviewing its developmental trajectory, conducting an in-depth analysis of its current research and application status, and offering perspectives on its future development trends. The aim is to provide a preliminary reference and insight for further research in this field.

1 The Origin and Evolution of Intelligent Fault Diagnosis Technology for Mechanical Equipment: Domestic and International Developments

As a systematic engineering technology, the modern prototype of mechanical equipment fault diagnosis can be traced back to the 1960s in the United States. The most milestone-driving force originated from the Apollo Program. During the implementation of this program, frequent failures of complex aerospace equipment posed severe challenges to the lunar landing mission. In response, the National Aeronautics and Space Administration (NASA) established the Mechanical Fault Prevention Group (MFPG), which is regarded as the formal beginning of systematic research on mechanical equipment fault diagnosis technology. The work of this group signified a transition for fault diagnosis from an "art" reliant on engineers' experience to a "science" based on data and analysis.

Over the next two to three decades, fault diagnosis technology entered a period of rapid development and industrial proliferation. Influenced by the radiating demands of the aerospace and military sectors, many international industrial giants, such as General Electric (GE) and Westinghouse Electric Corporation, began investing heavily in the research and development of specialized condition monitoring and fault diagnosis equipment. For instance, early diagnostic tools like vibration analyzers and oil spectrometric analyzers were successively introduced and commercialized. These initiatives demonstrated significant foresight, providing the technical reserves and practical paradigms for the large-scale promotion of Predictive and Health Management (PHM) in the civilian industrial sector later on, greatly advancing the technology from laboratory settings to industrial application [4-5].

While pioneering industrialized nations like the United States, Japan, and European countries were deeply integrating fault diagnosis technology into their industrial systems, China's related research started relatively late. It was not until the 1980s, with the deepening of reform and opening-up policies and the large-scale introduction of advanced foreign industrial production lines, that China's academic and industrial circles began systematically accessing and researching mechanical equipment fault diagnosis technology. Initially, this technology was primarily piloted in key industries vital to the national economy and people's livelihood, such as the chemical, metallurgical, and power industries, aiming to ensure the safe and stable operation of large-scale continuous production lines. Subsequently, its application scope rapidly expanded to high-end equipment fields including manufacturing, aerospace, and high-speed railways.

Particularly significant is that over the past two decades, accompanied by China's sustained economic growth and the strategic promotion of "Intelligent Manufacturing," fault diagnosis technology has encountered unprecedented development opportunities. Through deep industry-university-research collaboration, this technology has not only continuously caught up with the international forefront in theory but also achieved extensive promotion in engineering applications, solving numerous "critical bottleneck" issues in actual production. The benefits it brings are twofold: in terms of economic benefits, it creates substantial value for enterprises by reducing unplanned downtime and extending equipment lifespan; in terms of social benefits, it makes outstanding contributions to ensuring safe production and reducing the risk of major accidents. Consequently, it has gained widespread recognition and high importance from both the corporate sector and society at large.

2. Analysis of the Current Status of Intelligent Fault Diagnosis for Mechanical Equipment

After several decades of development, mechanical fault diagnosis has evolved into a relatively comprehensive and structured system, maturing into a well-established interdisciplinary field. Research in this domain continues to expand and diversify, primarily leveraging modern computational technologies. The core focus remains on monitoring the operational status of equipment and analyzing and diagnosing faults.

Through years of dedicated research and development, mechanical equipment fault diagnosis technology has achieved widespread adoption in industrial production and has permeated various high-tech sectors, including advanced manufacturing, aerospace, and energy systems. The general workflow of this technology is illustrated in Figure 1.
This integrated approach encompasses several key aspects: continuous condition monitoring through advanced sensor networks, sophisticated signal processing techniques for feature extraction, and the application of intelligent algorithms for accurate fault identification and prognosis. Furthermore, the integration with industrial automation systems enables real-time decision-making and facilitates predictive maintenance strategies, thereby significantly enhancing operational reliability and efficiency across multiple industries[6].

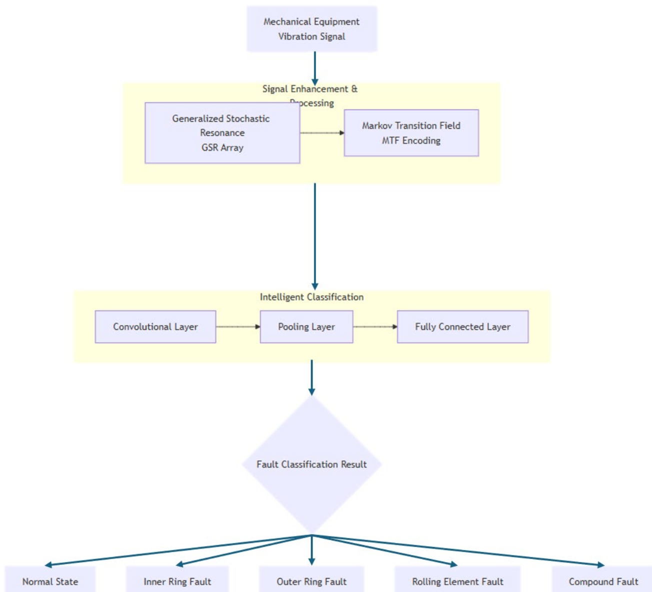

Fig 1. Technical Route for Fault Diagnosis

Building upon the solid foundation of widely adopted mechanical equipment condition monitoring and fault diagnosis technologies, the integration of AI has infused this field with revolutionary momentum. Specifically, AI technologies, represented by deep learning and machine learning, are driving a paradigm shift in fault diagnosis from traditional "signal analysis" and "model-driven" approaches towards "data-driven" and "intelligent decision-making" paradigms. The field of mechanical fault diagnosis has witnessed a surge in research and applications concerning ANNs, which possess the capability to autonomously learn complex fault characteristics and patterns from massive historical data. This enables the sensitive perception and precise classification of early-stage and subtle faults.
Although AI plays an increasingly central role in intelligent diagnosis systems, it is crucial to recognize that it does not exist in isolation. This advanced technology re-

mains deeply dependent on the traditional diagnostic technology framework. An efficient intelligent diagnosis system represents an organic fusion of three key elements: precision sensing technology, advanced signal processing techniques, and AI algorithms. It is precisely through the synergy of these multiple technological pathways that the accuracy, robustness, and real-time performance of diagnostic results are collectively enhanced. It is foreseeable that, driven by the continuous advancement of modern science and technology, intelligent fault diagnosis technology for mechanical equipment is progressing towards an optimistic trajectory of integration, automation, and intellectualization.

Concurrently, contemporary computing technology has achieved remarkable accomplishments. Particularly, the development of High-Performance Computing (HPC), edge computing, and cloud computing provides powerful computational support for processing the vast amounts of monitoring data generated in the diagnostic field. Leveraging these advantages, mechanical equipment fault diagnosis technology has reached a new level of sophistication, evolving into an independent, highly interdisciplinary comprehensive engineering discipline. Its core research focuses on equipment operational status monitoring, fault mechanism research, fault feature extraction, and intelligent identification, integrating knowledge from multiple fields such as mechanics, materials science, information science, and computer science. This discipline is increasingly becoming a focal point in industrial technological evolution and socio-economic development, gaining widespread recognition as an emerging technology capable of creating tangible value.

However, several bottlenecks and shortcomings remain to be addressed during its vigorous development. Firstly, there exists a contradiction between the universality and specificity of the technology. Different types of mechanical equipment exhibit significant variations in dynamic behavior and failure mechanisms. For instance, diagnostic methods based on stationary vibration signals are relatively mature for rotating machinery, but diagnostic accuracy and reliability for reciprocating machinery (e.g., internal combustion engines, reciprocating piston pumps), which have more complex motion forms and highly non-stationary signals, still require substantial improvement. Secondly, there is a gap between laboratory performance and field application. Many algorithms and systems that perform excellently in controlled laboratory environments often experience significant performance degradation when confronted with complex noise interference, harsh operating conditions, and variable loads at engineering sites. Furthermore, field diagnosis typically relies on precision instrumentation, which demands high operational expertise, poses deployment challenges, and incurs substantial costs, creating practical difficulties for rapid and flexible field engineering implementation.

Despite these challenges, the prospects for intelligent fault diagnosis technology for mechanical equipment are undoubtedly vast, considering the current demands of global industrial upgrading and social development. With the ongoing miniaturization and intellectualization of sensor technology, further optimization and light-weighting of algorithm models, and the low-latency data transmission capabilities offered by 5G communication technologies, this technology is poised for a new leap-frog development phase. It will not only profoundly transform industrial operation and maintenance models—progressing from "preventive maintenance" to "predictive maintenance" and ultimately achieving "autonomous health management"—but will also serve as a key enabling technology. This will drive the productivity and safety standards of the entire industrial society to new heights, thereby leading transformative changes in the socio-economic landscape. The specific workflow is illustrated in Figure 2.

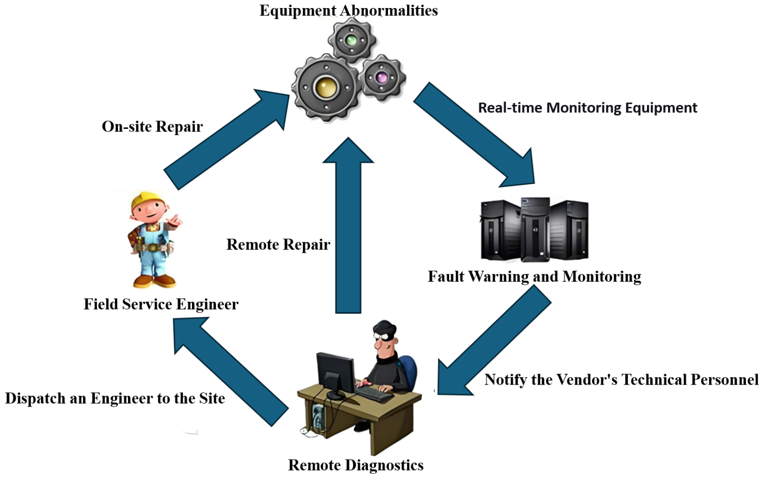

Fig 2. Fault Diagnosis Flowchart

3. Future Development Trends of Intelligent Fault Diagnosis Technology for Mechanical Equipment

As a cornerstone of modern industrial intelligent operations, the significance of mechanical equipment fault diagnosis technology is increasingly prominent. Its application scope is expanding from traditional heavy industries to cutting-edge fields such as precision manufacturing, new energy, and aerospace. Looking ahead, this technology will no longer be confined to the detection and diagnosis of single faults but will evolve towards a high-precision, self-adaptive, and fully interconnected intelligent ecosystem. Artificial intelligence will serve as the core driving force, promoting a shift in the diagnostic paradigm from "perceptual diagnosis" to "cognitive 预警," with its development exhibiting a systematic upward trajectory and trend of continuous improvement.

3.1. Towards High-Precision: From Macroscopic Vibration Analysis to Micro-Scale Damage Prediction

The future core competitiveness of fault diagnosis lies in the accurate perception and prediction capabilities for early-stage and weak faults. The key to this enhancement resides in improving signal processing accuracy and the level of multi-physical field fusion diagnosis[7].

Integration and Innovation of Advanced Signal Processing Algorithms:

Integration of Wavelet Theory and Deep Learning: In the future, time-frequency analysis techniques like wavelet transform will deeply integrate with deep learning models. For instance, utilizing wavelet packet decomposition for refined preprocessing of non-stationary vibration signals to extract multi-resolution features, which are then fed into Deep Belief Networks (DBNs) for identification, can significantly enhance the diagnostic accuracy for early-stage pitting in bearings, micro-cracks in gears, and other such faults[8].

Fractal Geometry and Health Indicator Construction: Fractal geometry will transcend simple feature extraction and be used to construct non-linear health indicators for equipment performance degradation. By calculating the long-term evolution trend of the fractal dimension of vibration signals, probabilistic prediction of the equipment's Remaining Useful Life (RUL) can be achieved, providing a quantitative basis for predictive maintenance.

Holospectrum and Manifold Learning: Holospectrum analysis will further integrate with non-linear dimensionality reduction techniques like manifold learning. This combination will automatically mine the low-dimensional intrinsic features that best characterize the equipment state from high-dimensional data amplitude, frequency, and phase information. This enables more accurate separation and identification of compound faults such as rotor misalignment and rubbing.

Prospective Application in Engine Joint Fault Diagnosis: Future solutions will no longer rely on single sensors. By deploying distributed optical fiber sensing networks (FBG) or Micro-Electro-Mechanical Systems (MEMS) sensor arrays at critical engine joints (e.g., blade tenon slots, flange connection surfaces), an "intelligent skin" can be formed. This allows for the synchronous acquisition and data fusion of multi-physical field information such as temperature, strain, and acoustic emission. Combined with the aforementioned advanced algorithms, the system will be capable of precisely locating micron-level clearance changes and predicting the initiation and propagation path of fatigue cracks based on physical models and data-driven models[9].

3.2. Towards High-Level Intelligence: From Expert Systems to Autonomous Decision-Making and Federated Learning

The development of intelligence will shift from building static knowledge bases to constructing "system intelligence" with continuous evolutionary capabilities[10].

From Expert Systems to Hybrid Augmented Intelligence: Traditional rule-based expert systems will evolve into hybrid augmented intelligent systems that combine deep learning with knowledge graphs. The knowledge graph is responsible for integrating prior knowledge such as equipment design principles, historical maintenance records, and physical failure models, while the deep learning model learns from real-time data. The mutual verification and enhancement between these two components endow the diagnostic decision-making process with both the efficiency of data-driven approaches and the interpretability of physical mechanisms.

Self-Evolving Knowledge Base and Federated Learning: Addressing the problem of data silos in industrial scenarios, Federated Learning (FL) will become a key technology. It allows different factories and different devices to collaboratively train a more powerful global diagnostic model without sharing local data. This not only protects data privacy but also enables the diagnostic model to utilize global knowledge for self-evolution, realizing a collective intelligence that becomes "smarter with use."

Digital Twin-Driven Reliability Enhancement: Digital Twin (DT) technology will provide a powerful simulation sandbox for fault diagnosis and prediction by constructing a virtual model that is fully synchronized with the physical equipment. The system can simulate various fault conditions and maintenance strategies within the digital twin, thereby verifying diagnostic logic and optimizing maintenance plans before actual faults occur. This significantly enhances the reliability of the technology and decision-making confidence.

3.3. Towards Deep Networking: From Stand-Alone Diagnosis to a Cloud-Edge-Client Collaborative Operation Ecology

Networking will reshape the implementation architecture of fault diagnosis, moving it from information silos towards full value chain collaboration.Empowerment by Industrial IoT and 5G/6G: Industrial Internet of Things (IIoT) technology enables the ubiquitous perception of the status of massive equipment, while 5G/6G networks, with their ultra-low latency and high reliability, provide the "neural network" for real-time remote diagnosis and control.

Cloud-Edge-Client Collaborative Diagnosis Architecture: The future diagnostic system will be an organic whole based on Cloud-Edge-Client collaboration. Client devices are responsible for data acquisition and lightweight edge intelligence diagnosis, achieving millisecond-level fault response. Edge computing nodes handle the aggregation of regional data and localized inference of complex models, ensuring data privacy and real-time performance. The Cloud diagnostic platform aggregates global data, performs large-scale model training, health status management, and operation and maintenance decision optimization, and continuously deploys the optimized models to the edge side.

Building a Predictive Maintenance Ecosystem: Through networked platforms, enterprises can seamlessly integrate diagnostic results with Enterprise Resource Planning (ERP) and Supply Chain Management (SCM) systems. When the system predicts that a component is about to fail, it can automatically trigger spare parts orders, dispatch service engineers, and optimize production schedules. Ultimately, this forms a closed-loop, efficient, intelligent operation and maintenance ecosystem centered on predictive maintenance, fundamentally enhancing the operational efficiency and reliability of modern industry.

4. Conclusion

Intelligent fault diagnosis technology for mechanical equipment serves as an indispensable core support for modern industrial systems, and its development level is directly related to the safety, economy, and sustainability of industrial operation. Through systematically reviewing the technology's development history,analyzing its current research status, and future trends, this paper draws the following conclusions:

Firstly, after decades of development, mechanical equipment fault diagnosis has evolved from initial experience-based maintenance methods into a comprehensive engineering technology system that deeply integrates multidisciplinary knowledge. This evolutionary process reflects the transformation in operation and maintenance philosophy from "reactive maintenance" to "preventive maintenance," and further towards "predictive maintenance." Particularly, the deep integration of artificial intelligence technology has propelled fault diagnosis to achieve a paradigm shift from "signal analysis" to "intelligent decision-making," significantly enhancing diagnostic accuracy, early warning capabilities, and automation levels.

Secondly, current intelligent diagnosis technology exhibits distinct characteristics of synergistic development across multiple technical pathways. The organic combination of intelligent algorithms based on deep learning with advanced signal processing techniques (such as wavelet analysis, fractal geometry, and holospectrum analysis) enables precise diagnosis of early faults in complex equipment. Simultaneously, the development of emerging technologies like high-performance computing and edge computing provides a solid computational foundation for processing massive monitoring data. However, it is also essential to recognize that the technology still faces significant challenges in practical application, including insufficient diagnostic accuracy for reciprocating machinery, limited adaptability to field environments, and the need for enhanced algorithm interpretability. These issues will become important directions for future research.

Looking ahead, intelligent diagnosis technology will develop towards higher precision, stronger intelligence, and deeper integration. In terms of high precision, the combination of multi-physical field sensing technology and advanced signal processing algorithms will enable the early identification and prediction of micro-damage. In terms of intelligence, the introduction of new technologies such as digital twins and federated learning will drive diagnostic systems towards self-learning and self-adaptive evolution. In terms of networking, the cloud-edge-client collaborative architecture based on the Industrial Internet of Things will build an intelligent operation and maintenance ecosystem spanning the entire value chain.

The future development of intelligent diagnosis technology requires not only innovative breakthroughs at the technical level but also the establishment of corresponding standard specifications systems, the strengthening of interdisciplinary talent cultivation, and the promotion of deep industry-university-research integration. Only through coordinated advancement across multiple dimensions—technological innovation, standard formulation, and talent training—can the full potential of intelligent diagnosis technology be realized, providing a solid guarantee for the safe and reliable operation of industrial equipment.

In summary, intelligent fault diagnosis technology for mechanical equipment is currently in a critical period of rapid development. With the continuous maturation of related technologies and the ongoing expansion of application scenarios, this technology is destined to bring revolutionary changes to modern industrial production, becoming an important force driving the high-quality development of the manufacturing industry and ensuring the stable operation of the national economy. Future research should pay more attention to the integration of theory and practice, deepening fundamental research while focusing on solving practical problems in engineering applications, thereby promoting the development of intelligent diagnosis technology towards greater precision, reliability, and practicality.

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