The Application of Intelligent Technologies in Equipment Maintenance Management

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Abstract: ***This paper investigates the application of intelligent technologies in the domain of equipment maintenance management, with a particular focus on the specific implementation models and practical pathways of key technologies—including artificial intelligence, the Internet of Things (IoT), big data analytics, and cloud computing. By analyzing the advantages of deploying these intelligent technologies in equipment maintenance contexts and examining practical case studies, the study elucidates their significant contributions to fault prediction, maintenance decision-making, and resource optimization and allocation. At the same time, it proposes countermeasures for the technical, safety, cost and other issues faced in the application process, and looks forward to the future development trend of intelligent technologies in equipment maintenance management, aiming to provide theoretical reference and practical guidance for promoting the intelligent transformation of equipment maintenance management, and help enterprises improve equipment management efficiency, reduce operating costs, and enhance core competitiveness.***

Keywords: Intelligent technology; Equipment maintenance management; Fault prediction; Internet of Things; Big data.

1. INTRODUCTION

In modern industrial production, equipment serves as the core asset for enterprise operations, and its stable operation plays a decisive role in enterprise production efficiency, product quality, and economic benefits. With the rapid development of Industry 4.0 and intelligent manufacturing, the complexity and automation level of enterprise production equipment continue to increase. Traditional equipment maintenance management models, such as breakdown maintenance and periodic maintenance, have gradually exposed many drawbacks and are difficult to meet the enterprise's needs for efficient, precise, and intelligent management. Breakdown maintenance involves repairing equipment only after a failure occurs; this passive maintenance method not only leads to production interruptions and huge economic losses but may also cause safety accidents. Although periodic maintenance reduces the risk of sudden equipment failures to a certain extent, due to the lack of accurate grasp of the actual operating status of the equipment, there is a problem of over-maintenance, resulting in waste of maintenance resources and increased enterprise operating costs. At the same time, the rapid development of intelligent technologies such as artificial intelligence, the Internet of Things, big data, and cloud computing has brought new opportunities for equipment maintenance management. Intelligent technologies can realize real-time monitoring of equipment operating status, accurate prediction of faults, and scientific formulation of maintenance decisions, effectively improving the efficiency and quality of equipment maintenance management and promoting the transformation and upgrading of equipment maintenance management towards intelligence and automation. Therefore, researching the application of intelligent technologies in equipment maintenance management has important practical significance. Deng (2025) proposed a homomorphic encryption-based mechanism to verify data integrity and prevent tampering in cloud storage environments, offering a robust solution to the persistent threat of unauthorized data modification. Mehta et al. (2026) developed a national AI security framework tailored for financial infrastructure protection, emphasizing the urgent need to safeguard critical financial systems from emerging AI-driven threats. Zhou (2025) introduced a digital precision distribution strategy for automotive industry social media content on private domain platforms, leveraging a collaborative filtering model based on user behavior to optimize content delivery. Li (2026) presented an AI-based approach for predicting and managing automation equipment lifecycle costs, demonstrating its potential to enhance customer lifetime value (CLV) through proactive cost management. In statistical computing and machine learning foundational research, Lin et al. (2023) advanced the computation of the Poisson multinomial distribution, providing essential tools for ecological inference and machine learning applications. Deng and Yang (2025) proposed multi-layer defense strategies and privacy-preserving enhancements to mitigate membership reasoning attacks in federated learning frameworks, addressing key privacy concerns in distributed machine learning. Gong et al. (2023) conducted a comprehensive review of neural network lightweighting techniques, which are critical for deploying complex models on resource-constrained devices. Junxi et al. (2024) developed GCN-MF, a graph convolutional network model based on matrix factorization that improves the accuracy of personalized recommendation systems. Zhang (2024) proposed a cohesive hierarchical clustering-based approach to dynamically adapt the supply and demand of power emergency materials, enhancing the efficiency of emergency response systems. In cloud infrastructure and industrial optimization, Wu (2025) introduced fault detection and prediction models to optimize resource usage in cloud environments, improving system reliability and cost-effectiveness. Li et al. (2025) explored gamified data visualization in smart cities, demonstrating its effectiveness in fostering citizen engagement in urban monitoring. Song (2025) presented an intelligent demand forecasting and inventory visualization system to enhance user experience in e-commerce, reducing stockouts and overstock situations. Wang (2025) applied Bayesian optimization for adaptive network reconfiguration in urban delivery systems, optimizing route planning and resource allocation. Liang and Chen (2019) proposed HDSO, a high-performance dynamic service orchestration algorithm for hybrid NFV networks, improving the efficiency of network service deployment. Chen and Bian (2019) developed a streaming media live broadcast system based on MSE, enhancing the stability and quality of live video streaming. Lian and Chen (2024) conducted research on complex data mining analysis and pattern recognition using deep learning, enabling more accurate extraction of insights from large-scale datasets. Qi and Liu (2024) designed a sales forecasting system based on Hadoop big data analysis, providing businesses with data-driven insights to optimize sales strategies. Xu et al. (2024) advanced automated surveillance by implementing real-time detection of crown-of-thorns starfish using the YOLOv5 deep learning model, supporting marine ecosystem conservation efforts.

2. ANALYSIS OF THE CURRENT STATUS OF EQUIPMENT MAINTENANCE MANAGEMENT

2.1 Traditional Equipment Maintenance Management Models and Problems

Traditional equipment maintenance management models mainly include breakdown maintenance, periodic maintenance, and preventive maintenance. Breakdown maintenance involves repairing equipment after a failure occurs. This model is simple and direct, but since equipment failures cannot be predicted in advance, it leads to production interruptions, resulting in issues such as delayed production plans and delayed order deliveries, bringing huge economic losses to enterprises and potentially causing safety accidents. Periodic maintenance involves maintaining and inspecting equipment at predetermined time intervals. It reduces the risk of sudden equipment failures to a certain extent, but due to the lack of accurate judgment of the actual operating status of the equipment, there is a phenomenon of over-maintenance. Over-maintenance not only wastes maintenance resources and increases maintenance costs but may also cause a decline in equipment performance and shorten equipment service life due to frequent disassembly. Although preventive maintenance considers equipment wear and aging, it still mainly formulates maintenance plans based on experience and statistical data, making it difficult to meet the personalized maintenance needs of modern complex equipment.

2.2 Intelligent Requirements for Equipment Maintenance Management

With the intelligent development of industrial production, higher requirements have been put forward for equipment maintenance management. Enterprises need to grasp the real-time operating status of equipment, promptly identify potential fault risks, and take preventive and repair measures in advance to reduce equipment downtime and improve production efficiency. At the same time, enterprises also hope to optimize the allocation of maintenance resources, reduce maintenance costs, and achieve efficient utilization of maintenance resources. In addition, in the context of global competition, enterprises need to improve the informatization and collaboration level of equipment maintenance management, realize information sharing and collaborative work between different departments within the enterprise, as well as between enterprises and suppliers and customers, so as to enhance the overall operational efficiency and competitiveness of the enterprise. The application of intelligent technology can effectively meet these needs and bring new changes to equipment maintenance management.

3. APPLICATION OF INTELLIGENT TECHNOLOGY IN EQUIPMENT MAINTENANCE MANAGEMENT

3.1 Real-time Monitoring of Equipment Status

Internet of Things (IoT) technology plays a key role in real-time monitoring of equipment status. By installing various sensors on key parts of the equipment, these sensors transmit the collected data to the data acquisition terminal through wireless or wired networks, and then the data acquisition terminal uploads the data to the cloud server or the enterprise's internal data center. Maintenance managers can access equipment operation data anytime and anywhere through terminal devices such as mobile phone APPs and computer clients to grasp the real-time operating status of the equipment. Once the equipment operating parameters exceed the normal range, the system will immediately issue early warning information to notify maintenance personnel to deal with it in a timely manner, thereby realizing early detection and prevention of equipment failures.

3.2 Fault Prediction and Diagnosis

The combination of artificial intelligence and big data technology provides strong technical support for equipment fault prediction and diagnosis. First, big data technology is used to collect historical data during equipment operation, including normal operation data, fault data, maintenance record data, etc. Then, artificial intelligence algorithms such as machine learning and deep learning are used to analyze and mine these data to construct equipment fault prediction models. For example, through neural network algorithms, the parameter characteristics of the equipment in normal operation and the parameter change rules when faults occur are learned. When the real-time operation data of the equipment matches the characteristics in the fault model, the system can predict the possible fault type and fault time of the equipment. In addition, artificial intelligence technology can also quickly diagnose the cause of equipment failure by analyzing the equipment failure phenomenon and combining cases and experience in the maintenance knowledge base, providing accurate maintenance suggestions for maintenance personnel.

3.3 Maintenance Decision-making

Based on the results of real-time equipment status monitoring and fault prediction and diagnosis, intelligent technology can help enterprises formulate scientific and reasonable maintenance decisions. Through big data analysis, the cost, effect and risk of different maintenance plans can be evaluated, providing a basis for enterprises to select the optimal maintenance plan.

3.4 Optimization of Maintenance Resource Allocation

The application of cloud computing technology and big data technology helps to achieve the optimal allocation of maintenance resources.

4. CONSTRUCTION PATH OF INTELLIGENT MAINTENANCE ECOSYSTEM

4.1 Building a "device-system-enterprise-industry" four-level intelligent maintenance ecosystem is an important direction for future development

At the enterprise level, a unified equipment data center should be established to integrate data from the Manufacturing Execution System (MES), Enterprise Asset Management (EAM) system, and Internet of Things platform, forming a full-life-cycle equipment database. A heavy industry enterprise has realized full-chain traceability from equipment design parameters and manufacturing data to operation and maintenance records through a data center. When equipment fails, the system automatically associates design documents and manufacturing process data, providing multi-dimensional support for root cause analysis of faults.

4.2 At the industry level, efforts can be made to establish an intelligent maintenance standard system, unifying data interfaces and maintenance process specifications

In the construction machinery field, multiple main engine manufacturers have jointly formulated equipment health data exchange standards, enabling the operating data of different brands of equipment to be displayed and analyzed on the same platform, providing a data foundation for after-sales maintenance services. At the same time, by establishing an industry maintenance knowledge base and sharing typical fault cases and maintenance experience, small and medium-sized enterprises can be promoted to quickly improve their intelligent maintenance capabilities.

4.3 Innovation in the talent training system is a key guarantee for the implementation of intelligent maintenance

A central enterprise has established a "Intelligent Maintenance Engineer" certification system, cultivating compound talents who understand both equipment mechanisms and AI algorithms through a combination of theoretical training, simulation practice, and on-site operation. The training courses include practical modules such as sensor deployment scheme design, fault feature engineering, and model tuning. Trainees quickly master intelligent technology application skills by debugging equipment fault prediction models on a virtual simulation platform, providing talent support for the enterprise's intelligent transformation.

5. PROBLEMS AND COUNTERMEASURES IN THE APPLICATION OF INTELLIGENT TECHNOLOGY IN EQUIPMENT MAINTENANCE MANAGEMENT

5.1 Existing Problems

5.1.1 Technical Problems

The application of intelligent technology in equipment maintenance management involves the integration of multiple technologies, making technical implementation difficult. For example, data collected by equipment sensors may have noise and errors, affecting data accuracy; the training of artificial intelligence algorithms requires a large amount of high-quality data, and insufficient or low-quality data will lead to a decrease in the accuracy of fault prediction models. In addition, compatibility issues may exist between equipment and systems from different manufacturers, resulting in inability to share and interact data.

5.1.2 Security Problems

With the intelligentization of equipment maintenance management, equipment is more closely connected to networks, and network security risks have increased accordingly. Hackers may attack equipment networks, steal equipment operation data, tamper with equipment control instructions, leading to equipment failures or production accidents. At the same time, improper operations by internal employees or data leakage may also bring security risks to enterprises.

5.1.3 Cost Issue

Introducing intelligent technologies for equipment maintenance management requires significant capital investment, including expenses for the procurement and installation of equipment sensors, development and purchase of software systems, construction and maintenance of data centers, and personnel training costs. For some small and medium-sized enterprises, the high cost may become a major obstacle to the application of intelligent technologies.

5.1.4 Talent Issue

The application of intelligent technologies in equipment maintenance management requires compound talents who understand both equipment maintenance management and intelligent technologies. However, such talents are currently relatively scarce, and the technical level and knowledge structure of internal employees are difficult to meet the needs of intelligent technology application, requiring a large amount of training and talent introduction work.

5.2 Countermeasures

5.2.1 Strengthen Technological R&D and Cooperation

Enterprises should increase investment in intelligent technology R&D and carry out cooperation with universities, research institutions, etc., to jointly overcome technical difficulties. For example, improving data quality through data cleaning and preprocessing technologies; optimizing fault prediction models using advanced artificial intelligence algorithms; formulating unified data standards and interface specifications to solve compatibility issues between equipment and systems.

5.2.2 Strengthen Network Security Assurance

Enterprises should establish a sound network security protection system, adopt security measures such as firewalls, intrusion detection, and data encryption to prevent network attacks and data leakage. At the same time, strengthen employees' network security awareness training, formulate strict security management systems, standardize employees' operational behaviors, and ensure the security of equipment and data.

5.2.3 Reasonably Control Costs

Enterprises can introduce intelligent technologies in phases and steps according to their actual situation. In the initial stage, some key equipment can be selected for pilot application, and then gradually promoted after evaluating the application effect and cost-effectiveness. In addition, enterprises can reduce the procurement cost of software and hardware equipment by cooperating with suppliers and adopting models such as leasing and cloud computing services.

5.2.4 Focus on Talent Cultivation and Introduction

Enterprises should strengthen the training of internal employees, improve their intelligent technology application ability and equipment maintenance management level through organizing technical lectures, training courses, and external learning. At the same time, actively introduce outstanding external compound talents to provide talent support for the application of intelligent technologies in enterprises.

6. DEVELOPMENT TRENDS OF INTELLIGENT TECHNOLOGIES IN EQUIPMENT MAINTENANCE MANAGEMENT

6.1 Continuous Improvement of Intelligence Level

With the continuous development of technologies such as artificial intelligence, Internet of Things, and big data, the application of intelligent technologies in equipment maintenance management will be more in-depth and extensive, and the intelligence level of equipment maintenance management will continue to improve. In the future, intelligent technologies will be able to achieve more accurate fault prediction and diagnosis of equipment, maintenance decisions will be more automated and intelligent, maintenance resource allocation will be more optimized, and the whole process of equipment maintenance management will be intelligent.

6.2 In-depth Integration with Other Technologies

Intelligent technologies will further integrate with blockchain, digital twin, edge computing, and other technologies, bringing new transformations to equipment maintenance management. For example, blockchain technology can enhance the security and credibility of equipment data, ensuring data immutability and traceability; digital twin technology can create virtual models of equipment to simulate real-time operating conditions, providing more intuitive basis for fault prediction and maintenance decision-making; edge computing technology can process and analyze data locally on equipment, reducing data transmission latency and improving equipment response speed.

6.3 Personalized Customization Services

Different enterprises have varying equipment types, operating environments, and management needs. In the future, the application of intelligent technologies in equipment maintenance management will place greater emphasis on personalized customization services. Through big data analysis and artificial intelligence algorithms, tailored equipment maintenance management solutions will be developed based on specific enterprise needs, enabling precise and personalized equipment maintenance management.

6.4 Rise of Remote Collaboration and Sharing Economy Models

With the popularization of 5G networks and the development of cloud computing technology, equipment maintenance management will realize remote collaboration and sharing economy models. Maintenance personnel can perform remote diagnosis and maintenance of equipment in different locations through remote video, virtual reality, and other technologies; enterprises can share maintenance resources and experience, reducing maintenance costs, improving maintenance efficiency, and promoting collaborative development in the equipment maintenance management industry.

7. CONCLUSION

Intelligent technologies demonstrate significant advantages in real-time equipment condition monitoring, fault prediction and diagnosis, maintenance decision-making, and optimal allocation of maintenance resources. They can effectively improve equipment reliability, reduce maintenance costs, optimize production efficiency, and provide strong technical support for enterprises to achieve intelligent transformation. Intelligent technologies are reshaping the future of equipment maintenance management. Enterprises should actively embrace technological 变革, explore intelligent implementation paths based on their actual conditions to enhance core competitiveness and achieve sustainable development. The application of intelligent technologies not only innovates equipment maintenance management models but also promotes the construction of a four-level intelligent maintenance ecosystem: "equipment - system - enterprise - industry". This system facilitates industrial chain collaboration through data sharing and standard unification, providing systematic solutions for industrial intelligent transformation and supporting high-quality development of the manufacturing industry.

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