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# Research and Development Prospects of the PHM Technology

**Junxi Yang**[1, *]

[1]School of Advanced Technology, Xi'an Jiaotong-Liverpool University, Suzhou, China

*Corresponding author: Junxi. Yang22@xjtlu.edu.cn

**Abstract:**

The good development of Prognostics and Health Management (PHM) technology can effectively realise the diagnosis of faults and improve the reliability and safety of product use. First of all, the importance of PHM and the relevant basic concepts and the gaps in the current development background, as well as the relevant sensor technology are introduced, and the use of multi-fusion sensor technology is mentioned; secondly, the feature extraction and related algorithms in PHM technology are introduced respectively, and the use of PHM technology in aviation technology is mentioned. Problems and solutions of innovation and inadequacy; finally, summarise and look forward to the research and development of PHM technology.

**Keywords:** PHM technology; fault diagnosis; sensor technology; feature extraction.

## 1. Introduction

The failure of the gear transmission system in an aero-engine can lead to the loss of power for the mechanical components of the entire aircraft system, thereby posing significant safety risks to the aircraft. Consequently, Prognostics and Health Management (PHM) is of great practical significance in monitoring the operational status of aero-engine gears and ensuring flight safety [1]. The increasing importance of PHM for mechanical equipment in modern industry and services stems primarily from the critical role that efficient equipment operation plays in enhancing productivity and economic efficiency for enterprises. With the advent of Industry 4.0 and smart manufacturing, companies are increasingly leveraging digital technologies, automation, and intelligent systems. PHM addresses the need for intelligent management by providing real-time monitoring, data analysis, and fault prediction capabilities. Moreover, the intensification of global economic competition compels companies to seek effective cost control measures; PHM can significantly lower operating costs by minimizing unplanned downtime and optimizing maintenance schedules. In industries such as aerospace and energy, where equipment reliability and safety are paramount, PHM enhances safety and reliability by identifying potential issues in a timely manner. Additionally, PHM can navigate the complexities of modern equipment systems and offer system-level maintenance strategies that comply with stringent regulatory and compliance requirements, thereby bolstering corporate reputation. Furthermore, in alignment with the promotion of sustainable development,

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PHM plays a vital role in minimizing resource waste and supporting green manufacturing practices. Thus, it is evident that PHM not only enhances the competitiveness of enterprises but also optimizes operations, making it an indispensable and crucial tool in the modern industrial and service sectors.

Predictive Health Management (PHM) is a maintenance strategy that leverages real-time equipment status and performance data to enhance maintenance management efficiency. By continuously monitoring and analyzing equipment health, PHM aims to predict potential failures. The primary objectives of PHM include reducing downtime, lowering maintenance costs, extending equipment lifespan, and increasing productivity. To achieve these objectives, PHM utilizes various sensor technologies, including temperature, vibration, and pressure sensors, to gather real-time data on equipment operations. This data is transmitted and stored in real time using Internet of Things (IoT) technology, often managed centrally on a cloud computing platform for subsequent analysis. For data analysis and modeling, advanced tools such as machine learning and artificial intelligence are employed to process the collected data and develop predictive models. These models identify potential failure modes and trends in equipment performance, thereby assisting technicians in making data-driven maintenance decisions.

Predictive Health Management (PHM) operates through a series of interconnected modules designed to effectively monitor and analyze equipment performance. First, the sensor module collects critical data, including parameters such as temperature, vibration, and pressure, serving as the „eyes and ears" of the system to assess the real-time status of the equipment. Once the data is collected, it undergoes pre-processing to enhance quality by filtering out noise and normalizing values, ensuring accuracy for subsequent analysis. Next, in the feature extraction phase, the system identifies and isolates key features within the data, allowing it to focus on the most relevant information to improve prediction accuracy. During the model training phase, various algorithms, such as deep learning and decision trees, are employed to analyze historical data and identify patterns that distinguish normal behavior from abnormal behavior. The error detection module plays a crucial role in maintaining operational integrity by continuously monitoring the equipment's state and identifying deviations from expected behavior. Finally, when potential errors are detected, the decision support system provides operators with valuable insights, including troubleshooting guides and maintenance recommendations, facilitating effective and efficient problem resolution. This structured workflow ensures optimal equipment performance and reliability.

Below is a diagram of how the system works:

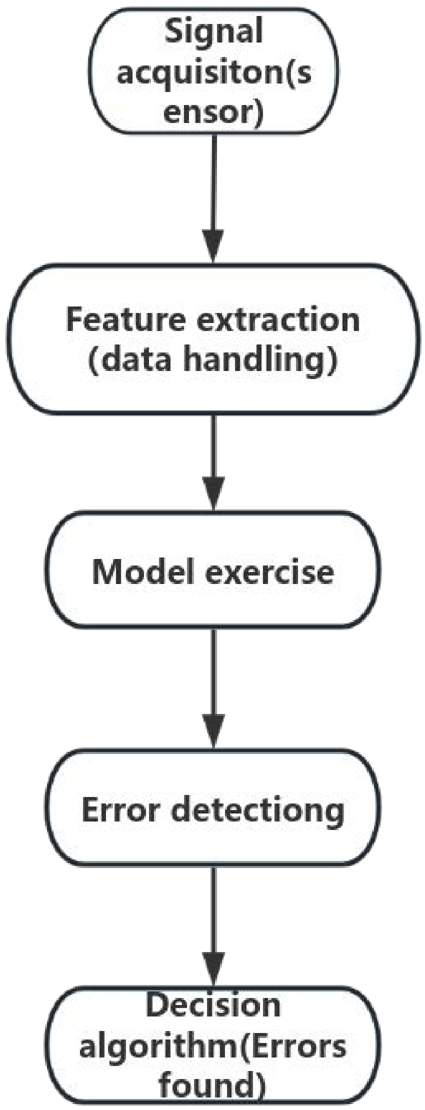


**Fig. 1 The PHM steps**

The limited research on the latest advancements in Predictive Health Management (PHM) technology highlights a significant area requiring further exploration. This study aims to address this gap by systematically analyzing and summarizing existing technologies while identifying key challenges and development trends. Our goal is to establish a clear research direction for PHM in the context of mechanical equipment. We anticipate that the in-depth analysis presented in this study will not only provide theoretical support and practical guidance for related fields, but also contribute to the enhancement of intelligence and reliability in mechanical equipment, ultimately fostering positive advancements in the industry.

## 2. Application of sensors in PHM technology

### 2.1 Vibration sensors

Vibration sensors play a crucial role in Predictive Health Management (PHM) by analyzing the health status of equipment and identifying potential failures in advance through the monitoring of vibration signals from mechanical systems. In fault diagnosis, vibration sensors assess the operating state of equipment, utilizing time and frequency domain analysis techniques to extract features. These features are then compared to normal operating conditions to identify failure modes such as imbalance, misalignment, looseness, and gear failure. Through long-term monitoring of vibration signals, coupled with data analysis and machine learning, vibration sensors facilitate predictive maintenance by estimating the Remaining Useful Life (RUL) of equipment and forecasting potential downtime. This capability allows for the dynamic adjustment of maintenance schedules, thereby reducing equipment downtime. Additionally, continuous monitoring of vibration characteristics enables real-time assessment of operating conditions, ensuring that equipment operates optimally and mitigating the risk of unplanned downtime due to abnormal vibrations. The integrated application of vibration sensors also enhances equipment health assessment. By combining vibration analysis with data from other sensors (e.g., temperature, pressure), organizations can make informed management decisions. Furthermore, by analyzing vibration signals and identifying anomalies associated with production processes, companies can optimize operational parameters, improving productivity and product quality. Overall, the application of vibration sensors in PHM provides substantial support for equipment fault diagnosis, predictive maintenance, and condition monitoring, facilitating better management of equipment health, reducing maintenance costs, and enhancing productivity.

### 2.2 Visual sensors

Visual sensing technology operates through several key stages. First, image acquisition involves capturing ambient light signals using a camera or other image sensors and converting these signals into a digital image. The quality of this acquisition directly influences subsequent processing and is dependent on factors such as illumination and resolution. Next, in the pre-processing stage, the acquired images undergo various enhancements, including de-noising, brightness and contrast adjustments, and distortion corrections, all aimed at improving image quality. This step is crucial for enhancing the robustness and accuracy of the subsequent algorithms. Following pre-processing, the feature extraction stage identifies key attributes from the image, such as edges, texture, and color. During this stage, image information is converted into quantifiable feature vectors through filtering and transformation techniques, facilitating easier processing. The fourth stage involves target identification and classification, where targets within an image are classified and identified by comparing the extracted features of the input image with known targets using established feature models or machine learning algorithms. Finally, the target tracking and localization stage enables continuous monitoring and precise positioning of identified targets, ensuring effective analysis and response. Together, these stages form a robust framework for visual sensing, allowing for comprehensive image analysis and interpretation.

However, single sensors exhibit certain limitations in various scenarios. For instance, vibration sensors may encounter noise interference when identifying specific frequencies or modes, while vision sensors often struggle under low light conditions or in complex environments. To address these limitations, contemporary solutions increasingly favor the use of multi-sensor fusion techniques. By integrating different types of sensors, systems can synthesize data from each source, leveraging their respective strengths to enhance overall detection accuracy and reliability. For example, combining data from visual sensors and vibration sensors enables a more comprehensive understanding of equipment status and environmental changes, leading to more accurate judgments and responses. Similarly, merging optical and thermal sensors can address deficiencies in spark detection, as optical sensors are highly sensitive to variations in lighting conditions, while thermal sensors can be influenced by environmental factors. Additionally, traditional water spray control systems often lack intelligent control capabilities to adjust to the actual conditions of a fire, which may result in resource wastage or inadequate suppression. Multi-sensor fusion technology offers innovative solutions for fire detection. By integrating information from different sensors, the accuracy and reliability of detection can be significantly improved [2]. This approach not only enhances system performance but also facilitates better adaptation to complex and dynamic operating environments. Furthermore, the incorporation of novel sensor technologies, such as laser sensors for high-precision distance measurements, can further strengthen the effectiveness of multi-sensor fusion systems.

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## 3. Feature Extraction

Feature extraction is a crucial step in data preprocessing, particularly in the domains of machine learning and shape recognition. Its primary purpose is to extract valuable information from raw data for subsequent analysis and modeling. Feature extraction techniques exhibit several key characteristics. Firstly, they possess the ability to reduce dimensionality, transforming high-dimensional data into more compact representations. This reduction not only decreases data storage complexity but also enhances computational efficiency. Throughout this process, feature extraction emphasizes the preservation of information, ensuring that critical details are retained and do not adversely impact subsequent analyses.

Secondly, feature extraction enhances model performance by extracting effective features, thereby increasing the accuracy of machine learning models and minimizing overfitting. Additionally, it includes a noise reduction capability that aids in eliminating noise from the data and extracting useful signals, ultimately improving data quality. The feature extraction method is highly adaptable to various types of data and application scenarios, including image processing, text analysis, and speech signal processing. Moreover, certain feature extraction techniques, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), offer interpretability of the features, aiding in the understanding of data structures. To date, the PCA-LDA statistical analysis method based on ATR-FTIR spectroscopy has been widely employed in the detection and identification of significant differences in substance structure. This approach provides a valuable reference for the study of hemp fiber identification using infrared spectroscopy [3].

Feature extraction techniques exhibit considerable diversity, encompassing both conventional statistical features (such as mean and variance) and more sophisticated methods from deep learning, including the feature extraction layers of convolutional neural networks. These methods vary in computational complexity; deep learning approaches, like convolutional layers, often demand significant computational resources, while simpler methods, such as Fourier transforms in the frequency domain, are less demanding. In Prognostics and Health Management (PHM), feature extraction plays a critical role in signal data analysis and typically includes time domain features, frequency domain features, and time-frequency features. Time domain features are directly derived from time series signals, reflecting temporal changes and often include metrics like mean, variance, skewness, and kurtosis. These features are particularly suitable for signals that exhibit steady-state behavior or short-term variations and are widely applied in machine condition monitoring and fault detection, such as identifying anomalies in motor vibration signals [4]. Frequency domain features analyze the signal's characteristics through Fourier transforms, capturing elements like power spectral density, frequency components, and amplitude. These features are effective for assessing periodic signals and identifying harmonics and fault frequencies, such as in the diagnosis of gear and bearing faults. Conversely, time-frequency features integrate information from both time and frequency domains by employing techniques such as the short-time Fourier transform or wavelet transform. These features are ideal for analyzing non-stationary signals, allowing for the examination of spectral changes at different time points. They are particularly useful in monitoring and diagnosing complex signals, such as in the health assessment of aviation engines. Choosing appropriate feature extraction methods can significantly enhance the accuracy and effectiveness of PHM systems. Additionally, feature extraction techniques must account for domain specificity, as different domains may exhibit distinct characteristics; thus, careful design and selection are essential for specific applications. Finally, advanced feature extraction techniques, such as kernel methods, can effectively capture nonlinear relationships within the data, further improving model performance.

## 4. Algorithms in PHM

In Predictive and Health Management (PHM), algorithms can be categorized into classification algorithms and prediction algorithms, both of which play crucial roles in equipment fault detection and remaining useful life (RUL) prediction. Classification algorithms are primarily used to determine whether a device is malfunctioning and to identify its specific type by analyzing feature data and assigning it to predefined categories. Typical classification algorithms include Support Vector Machines (SVMs), which are effective for diagnosing machinery faults such as bearing and gear failures [5]; decision trees, which are intuitive and easy to interpret; and random forests, an ensemble learning method that constructs multiple decision trees and aggregates their votes to enhance classification accuracy and robustness. Random forests are widely utilized in monitoring the condition of industrial equipment. Additionally, neural networks, particularly Convolutional Neural Networks (CNNs), are commonly used for identifying fault types in wind turbines [5], while Recurrent Neural Networks (RNNs) excel in handling complex nonlinear relationships and time-series data, making them suitable for fault classification in aero-engine health monitoring [6]. On the other hand, prediction algorithms are primarily focused on forecasting the Remaining Useful Life (RUL) of equipment based on historical data and current states, utilizing statistical and machine learning techniques for life prediction. Common prediction algorithms include linear regression, which is appropriate for simple linear models, such as predicting the remaining life of batteries, and time series analysis methods like the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA performs future value predictions by analyzing the trends and seasonal patterns within time-series data, making it suitable for datasets exhibiting time dependency.

## 5. Application of PHM in aircraft

The machining centre is an important system in the production of aviation equipment, which is mainly used to manufacture hull structures and important engine parts. In order to meet the requirements of large orders, aviation manufacturing companies are usually equipped with three- and five-axis vertical machining centres for large portals. In this process, the PHM system of the machining centre is crucial for improving production efficiency.

The PHM system uses the “Cloud + Terminal” technical architecture to install vibration sensors and current sensors on the device side for real-time data collection [7]. The vibration sensor can monitor the wear and failure of the ball thread, guide rail and lubrication system, while the current sensor is used to detect problems such as spindle symmetry, engine failure and wave bending. After data cleaning and conversion, the collected effective production data is uploaded to the cloud for management via PC or mobile devices.

The built-in model of the PHM system can automatically calculate the comprehensive efficiency (OEE) of the equipment, count the downtime, identify the defect status of map parts and use intelligent decision algorithms to realise fault identification and forecasting. The system also supports the analysis of fault alert data, the statistics of the frequency of different alarm types through historical data and optimises the warning threshold in combination with machine learning algorithms to improve the intelligence level for operation and maintenance. Implementing and operating a Prognostics and Health Management (PHM) system for machining centers involves several challenges that must be addressed to maximize its benefits. Firstly, the accuracy and reliability of installed sensors, such as vibration and vision sensors, are crucial; improperly calibrated or low-quality sensors can result in inaccurate predictions and evaluations. Secondly, environmental factors like temperature and humidity can introduce noise into the data, complicating the analysis. Additionally, managing the vast amounts of data generated by continuous monitoring presents another challenge, as data overload can lead to critical insights being overlooked and inaccuracies that affect decision-making.

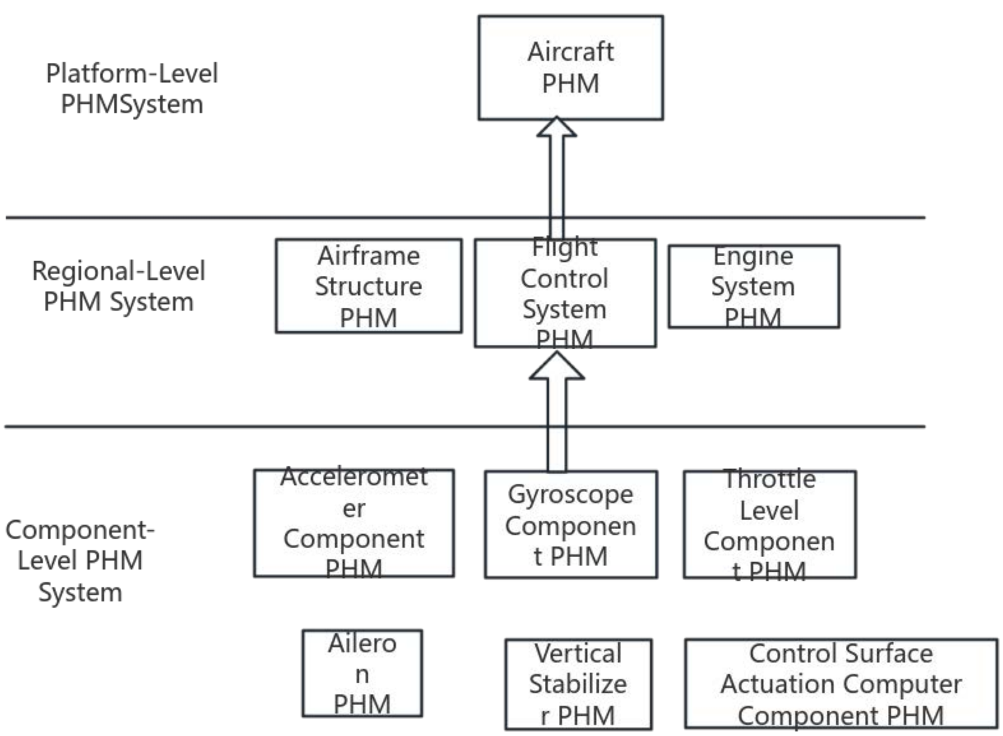


**Fig. 2 The PHM structure of the aircraft [8]**

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Predictive models within the system may lack robustness if they rely on outdated historical data. Without regular updates, these models may not accurately reflect current operating conditions. Additionally, if the training data is not representative, biases in machine learning algorithms can result in overfitting, diminishing their effectiveness in real-world applications. User training is essential; without a sufficient understanding of the system, users may misinterpret the data, leading to unnecessary maintenance operations or the oversight of critical information. Furthermore, integration with existing manufacturing processes can be complex, and any disconnect between PHM insights and operational practices may hinder the adoption of predictive maintenance strategies.

Additionally, if alerts do not prompt timely maintenance, operations may revert to a reactive maintenance model, where issues are addressed only after significant downtime or damage occurs. While PHM systems are intended to enhance efficiency, frequent maintenance alerts or overly cautious decision-making can negatively impact overall productivity. Finally, reliance on cloud services for data management raises concerns regarding cloud reliability and data security.

## 6. Conclusion

This paper discusses the shortcomings of current PHM technologies by introducing relevant sensing technologies, accompanied by examples and suggested improvements. It subsequently illustrates specific cases of PHM systems. The continuous updates and iterations of new-generation information technologies—including big data analysis, sensors, the Internet of Things (IoT), the Internet, and artificial intelligence—are transforming the production systems of manufacturing enterprises and injecting new vitality into the development of PHM technologies. Despite the rapid advancements in PHM technology, significant gaps remain due to varying environments and diverse needs that require further research. Therefore, it is essential to establish a reliable PHM system that aligns with the characteristics of the specific objects involved, along with the development of a PHM-related evaluation system. This approach will promote the rationalization, standardization, and scientific advancement of PHM technologies.

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