**International Journal of Advanced Engineering and Technology Research**
ISSN: 3106-8677 (Print), ISSN: 3106-8685 (Online) | Vol. 2, No. 2, 2026

# Performance Optimization of Intelligent Sensor Monitoring System for Industrial Mechanical Equipment Based on Improved Algorithm

**Mengchen Zou**

The University of Hong Kong, School of Professional and Continuing Education Community College, China

**Abstract:** With the rapid development of industrial Internet of Things (IIoT) and intelligent manufacturing technology, intelligent sensor monitoring systems have been widely applied in the condition monitoring and fault early warning of industrial mechanical equipment. However, traditional monitoring systems suffer from prominent problems such as low data processing efficiency, high transmission delay, poor anti-interference ability and low fault recognition accuracy in complex industrial working conditions, which seriously restrict the real-time performance and stability of equipment state monitoring. To solve the above defects, this paper proposes an improved hybrid optimization algorithm based on variational mode decomposition (VMD) and adaptive weighted ensemble learning, and applies it to the performance optimization of industrial mechanical equipment intelligent sensor monitoring system. Firstly, the system overall architecture is optimized, and a hierarchical data processing framework of edge acquisition, real-time processing and cloud analysis is constructed to reduce data transmission pressure. Secondly, aiming at the noise interference and redundant data of sensor vibration, temperature and current signals in industrial environments, an improved VMD algorithm with adaptive penalty factor is designed to realize efficient denoising and feature extraction of monitoring data. Finally, an adaptive weighted ensemble fault detection model is established to optimize the data analysis and state recognition performance of the monitoring system. Experimental results show that compared with the traditional system, the improved monitoring system reduces the data processing delay by 41.6%, improves the signal denoising signal-to-noise ratio (SNR) by 3.8 dB, and increases the equipment fault recognition accuracy to 96.2%. The optimized system has better real-time performance, stability and detection accuracy, which can effectively meet the high-precision and real-time monitoring requirements of industrial mechanical equipment under complex working conditions.

**Keywords:** Intelligent sensor monitoring system, hierarchical architecture, edge-cloud collaboration, data acquisition, industrial mechanical equipment, performance optimization.

## 1. Introduction

Industrial mechanical equipment serves as the fundamental core carrier supporting modern industrial production. Its running condition exerts a direct influence on corporate production efficiency, operational safety and economic profit. Long-duration continuous operation, fluctuating load impact and harsh industrial surroundings commonly trigger component abrasion, part aging and unexpected failures, which may trigger production suspension and severe safety incidents. Equipped with intelligent sensors, the monitoring system can perceive, gather and analyze real-time operational parameters including vibration, temperature, pressure and current. It has evolved into a vital technical approach for equipment status tracking, fault identification and predictive maintenance across industrial sectors [1].

In recent years, with the popularization of MEMS sensors, wireless communication technology and artificial intelligence algorithms, intelligent sensor monitoring systems have achieved rapid iterative development. Traditional monitoring systems mostly adopt fixed threshold judgment and single algorithm analysis, which have great limitations in practical industrial application. On the one hand, industrial sites have complex electromagnetic interference and environmental noise, resulting in a large amount of noise and redundant data in sensor monitoring signals, which affects the accuracy of feature extraction [2]. On the other hand, the traditional centralized data processing mode leads to large network transmission pressure and high system delay, unable to meet the real-time early warning requirements of sudden equipment faults [3]. In addition, single machine learning and signal processing algorithms have poor adaptability to variable industrial working conditions, low fault recognition efficiency and easy misjudgment and omission, which cannot adapt to the high-precision monitoring needs of large-scale industrial mechanical equipment clusters [4].

To solve the above problems, domestic and foreign scholars have carried out a series of research on the optimization of industrial sensor monitoring systems. Some studies optimize the system hardware architecture by adopting edge computing technology to realize local data processing and reduce cloud transmission delay [5]. Some researches focus on signal processing algorithm optimization, using empirical mode decomposition (EMD) and wavelet transform to denoise sensor signals and improve signal purity [6]. However, EMD is prone to modal aliasing and endpoint effects, and wavelet transform relies heavily on artificial parameter setting, with poor adaptive performance. The traditional VMD algorithm has stable decomposition performance, but its fixed penalty factor cannot adapt to time-varying industrial signals, resulting in incomplete feature extraction [7]. At present, most optimization schemes only optimize a single link of the system, lacking systematic optimization of data acquisition, processing, analysis and fault recognition, and the overall system performance improvement is limited.

Accordingly, this paper develops a complete and systematic performance optimization solution targeting the intelligent sensor monitoring system used for industrial mechanical equipment. To tackle signal distortion and ineffective feature extraction under complex working conditions, an improved VMD algorithm with adaptive penalty factor is adopted to conduct high-quality signal denoising and feature enhancement. Together with the adaptive weighted ensemble learning model, the overall fault detection and diagnosis capability is greatly strengthened. In addition, the layered system framework is reasonably adjusted to achieve seamless combination of real-time edge data processing and in-depth cloud intelligent analysis. This integrated design effectively elevates the system response speed, anti-interference resilience and fault identification precision. The research outcomes can offer practical technical references and design ideas for stable, efficient and high-performance operation of industrial intelligent monitoring systems.

# 2. Overall Architecture of Optimized Intelligent Sensor Monitoring System

Aiming at the prominent drawbacks existing in traditional industrial equipment monitoring systems, including obvious data transmission delay, unsatisfactory detection precision and weak operational stability under complicated working environments, this paper carries out targeted structural upgrading and performance optimization for the whole monitoring framework. A complete three-layer hierarchical system structure is established, consisting of perception layer, edge processing layer and cloud analysis layer. This layered design covers every key link from original data collection, real-time signal transmission, local data processing to deep intelligent analysis. It effectively standardizes data flow rules and rationalizes task allocation of each functional module, so as to achieve comprehensive performance improvement throughout the whole monitoring procedure.

## 2.1. Perception Layer Optimization

The perception layer is responsible for real-time collection of operating state data of industrial mechanical equipment, including vibration, surface temperature, operating current, operating pressure and other key parameters. Traditional perception layer adopts single sensor layout and fixed-frequency acquisition, which has low data coverage and serious data redundancy. In this optimization scheme, multi-type high-precision intelligent sensors are deployed in key parts of equipment such as bearings, gears and motors, including MEMS vibration sensors, digital temperature sensors and current sensors [8]. Meanwhile, an adaptive frequency acquisition strategy is adopted: when the equipment operates stably, the low-frequency acquisition mode is enabled to reduce redundant data generation; when the signal fluctuation exceeds the threshold, the high-frequency acquisition mode is automatically switched to capture transient fault features, which effectively balances data comprehensiveness and data volume.

## 2.2. Edge Processing Layer Optimization

The edge processing layer is the core link of system performance optimization, which undertakes the tasks of real-time signal denoising, feature extraction and preliminary fault judgment. Different from the traditional centralized cloud processing mode, the optimized system pushes the real-time data processing task to the edge node, uses the improved VMD algorithm to process the original sensor data locally, removes noise and redundant information, extracts effective equipment state features, and only uploads feature data and abnormal data to the cloud platform. This mode greatly reduces network transmission pressure and effectively reduces system transmission and processing delay. At the same time, the edge node is equipped with a lightweight fault detection model, which can realize real-time early warning of sudden faults and improve the system response speed.

## 2.3. Cloud Analysis Layer Optimization

The cloud analysis layer is responsible for deep data mining, fault classification and system parameter optimization. Based on the feature data uploaded by edge nodes, the adaptive weighted ensemble learning model is used for deep analysis to realize accurate identification and classification of different types of equipment faults. Meanwhile, the cloud platform stores historical monitoring data, builds an equipment health state database, realizes equipment life prediction and predictive maintenance decision-making, and continuously optimizes the algorithm model parameters according to long-term monitoring data to improve the adaptive performance of the system for different working conditions.

# 3. Improved Algorithm Principle and Optimization Design

The core of system performance optimization is the improvement of signal processing and fault diagnosis algorithms. This paper proposes an improved adaptive variational mode decomposition (IA-VMD) algorithm for sensor signal denoising and feature extraction, and constructs an adaptive weighted ensemble learning (AWEL) model for equipment fault recognition, so as to solve the problems of poor denoising effect and low fault recognition accuracy of traditional algorithms.

## 3.1. Improved Adaptive VMD Algorithm

The traditional VMD algorithm decomposes the original signal into several intrinsic mode functions (IMFs) by constructing a variational constraint model, which has good non-stationary signal processing ability. However, its penalty factor and decomposition number are fixed values set artificially, which cannot adapt to the time-varying and noisy industrial sensor signals, resulting in incomplete feature extraction or over-decomposition [9]. Aiming at this problem, this paper designs an adaptive penalty factor updating strategy based on signal SNR, and realizes adaptive optimization of decomposition parameters.

Firstly, the SNR of the real-time collected sensor signal is calculated. When the signal SNR is low and the noise interference is serious, the penalty factor is adaptively increased to enhance the noise suppression ability; when the signal SNR is high and the effective features are prominent, the penalty factor is appropriately reduced to retain weak fault features. The adaptive update formula of the penalty factor is as follows:

$$\alpha_{new}=\alpha_0\times\frac{SNR_0}{SNR+1}$$

Where $\alpha_{new}$ is the optimized penalty factor, $\alpha_0$ is the initial penalty factor, $SNR_0$ is the reference signal-to-noise ratio, and SNR is the real-time signal signal-to-noise ratio.

Meanwhile, the number of decomposition modes is automatically determined according to the signal frequency domain distribution, which avoids modal under-decomposition and over-decomposition. The improved IA-VMD algorithm can adaptively adjust parameters according to different industrial signal characteristics, effectively remove environmental noise, and accurately extract weak fault feature information of equipment.

### 3.2. Adaptive Weighted Ensemble Learning Model

In view of the problem that single machine learning model has poor generalization ability and low fault recognition accuracy in complex working conditions, this paper constructs an adaptive weighted ensemble learning model integrating K-nearest neighbor (KNN), support vector machine (SVM) and random forest (RF). The model assigns different weights to each base learner according to the real-time recognition accuracy of different fault samples, and realizes weighted fusion of recognition results, which makes up for the defect of single model and improves the accuracy and robustness of fault diagnosis [10].

The model first uses the IA-VMD algorithm to extract multi-dimensional feature parameters such as signal amplitude, frequency, energy and entropy, and constructs a fault feature dataset [11], Then, the three base learners are trained respectively, and the real-time prediction accuracy of each base learner on different fault types is calculated. The weight coefficient of each model is dynamically updated according to the accuracy, and the final fault classification result is obtained by weighted voting. The adaptive weight update formula is:

$$w_i = \frac{Acc_i}{\sum_{i=1}^{n} Acc_i}$$

Where $w_i$ is the weight of the i-th base learner, $Acc_i$ is the real-time recognition accuracy of the i-th model, and $n$ is the number of base learners. The ensemble model can dynamically adjust the weight of each algorithm according to different fault features, giving full play to the advantages of different models, and significantly improving the accuracy of equipment fault recognition under complex and variable working conditions.

## 4. Experimental Verification and Result Analysis

### 4.1. Experimental Setup

To verify the optimization effect of the improved algorithm and the optimized monitoring system, this paper builds an experimental platform based on industrial gearbox and bearing rotating machinery equipment. The experimental equipment is equipped with vibration, temperature and current sensors to collect operating data under normal operation, bearing wear, gear abrasion and motor overload faults. The experimental environment simulates industrial electromagnetic interference and environmental noise, and compares and tests the traditional monitoring system and the optimized system in terms of signal denoising effect, data processing delay and fault recognition accuracy.

### 4.2. Signal Denoising Performance Analysis

The traditional EMD, wavelet transform, traditional VMD and improved IA-VMD algorithms are used to denoise the collected equipment vibration signals, and the SNR and root mean square error (RMSE) are used as evaluation indexes. It can be seen that the improved IA-VMD algorithm has the highest SNR and the lowest RMSE. Compared with the traditional VMD algorithm, the SNR is increased by 3.8 dB, and the RMSE is reduced by 0.021. This indicates that the improved algorithm has better noise suppression ability and can retain more effective fault feature information, which provides high-quality data support for subsequent fault diagnosis.

### 4.3. System Real-time Performance Analysis

The data processing delay of the traditional centralized processing system and the optimized edge-cloud hierarchical processing system under different data volumes is tested. The experimental results show that with the increase of monitoring data volume, the delay of the traditional system increases exponentially, while the delay of the optimized system increases slowly. Under the condition of 1000 groups of sensor data, the average processing delay of the traditional system is 42.5 ms, while that of the optimized system is only 24.8 ms, with a delay reduction rate of 41.6%. The optimized system realizes local processing of data through edge computing, effectively reduces network transmission pressure, and significantly improves the real-time response speed of the system.

### 4.4. Fault Recognition Accuracy Analysis

Four common equipment states (normal operation, bearing wear, gear abrasion, motor overload) are identified by using single SVM, single RF, traditional ensemble model and improved AWEL model respectively. The experimental results show that the fault recognition accuracy of the improved AWEL model reaches 96.2%, which is 8.5% higher than that of single SVM model and 4.3% higher than that of traditional fixed-weight ensemble model. The improved model can dynamically adapt to different fault feature distributions, effectively avoid misjudgment caused by single model limitations, and greatly improve the overall fault diagnosis accuracy of the monitoring system.

## 5. Conclusion and Prospect

Aiming at the prominent defects of traditional intelligent sensor monitoring systems for industrial mechanical equipment, including insufficient real-time data processing performance, weak environmental anti-interference capability, and low accuracy of equipment fault identification in complex industrial scenarios, this paper proposes a comprehensive system performance optimization scheme integrating improved variational mode decomposition (VMD) and adaptive weighted ensemble learning algorithm. To address the excessive transmission delay caused by the traditional centralized cloud processing mode, the optimized system adopts a novel edge-cloud hierarchical collaborative architecture, which distributes real-time signal preprocessing and preliminary fault judgment tasks to local edge nodes, effectively reducing cloud network transmission pressure and greatly cutting down system data transmission and processing delay. Targeting the problem that industrial complex noise and signal interference easily submerge weak equipment fault features, the designed improved IA-VMD algorithm realizes adaptive adjustment of decomposition penalty factors according to real-time signal SNR, achieving efficient signal denoising, noise separation and accurate extraction of subtle fault feature information from noisy sensor monitoring data. On this basis, the constructed adaptive weighted ensemble learning model dynamically optimizes the weight of multiple basic learners according to the fitting effect of different fault samples, which makes up for the poor generalization and low recognition stability of single machine learning models. A series of comparative experiments fully verify that the optimized intelligent monitoring system possesses significant superiorities in signal denoising quality, real-time response efficiency and fault diagnosis accuracy. It can stably adapt to variable load, electromagnetic interference and other complex industrial working conditions, effectively satisfying the high-precision, real-time and stable operation requirements of intelligent monitoring for modern industrial mechanical equipment.

In view of the existing limitations of the current research, there is still room for further optimization and improvement of the monitoring system and algorithm in subsequent studies. Firstly, the structural complexity and computational overhead of the improved hybrid algorithm will be further optimized to simplify model iteration and calculation steps, reduce hardware operation consumption, and realize lightweight, low-power and high-efficiency deployment on more miniature edge sensing devices. Secondly, the system functional framework will be expanded to support multi-device cluster synchronous monitoring and collaborative analysis, so as to adapt to the large-scale and integrated operation mode of modern industrial equipment. In addition, combining advanced deep learning feature mining technology and digital twin virtual mapping technology, the research will further build a high-precision equipment health prediction model, break through the limitations of traditional post-fault diagnosis, effectively improve the accuracy of equipment predictive maintenance, and finally realize full-life cycle intelligent perception, real-time early warning, accurate diagnosis and scientific management of industrial mechanical equipment, providing more reliable technical support for intelligent and safe production in industrial fields.

# References


[1] Xue, Q. Q., Bai, L. M., & Zhongneng, Y. (2025). Application of Intelligent Sensor in Condition Monitoring of Electromechanical Equipment. Industrial Equipment and Technology, 8(2), 45–50.

[2] Zhang, Y., Wang, J., & Li, H. (2024). Smart Sensor-Based Monitoring Technology for Machinery Fault Detection. Sensors, 24(12), 2470–2485. https://doi.org/10.3390/s24122470

[3] Liu, X., & Chen, T. (2025). Real-time Data Processing of Electromechanical Sensors in Intelligent Manufacturing Systems. Scientific Atlas, 15(3), 112–118.

[4] Wang, L., & Zhang, H. (2026). An optimized ensemble framework for machinery fault detection in IoT environments. Journal of Intelligent Manufacturing, 37(2), 289–302. https://doi.org/10.1007/s10845-025-02156-9

[5] Li, M., & Yang, S. (2025). Edge AI-Based Real-time Anomaly Detection for Industrial Vibration Monitoring System. Electronics World, 31(7), 56–62.

[6] Zhao, J., & Zhou, Y. (2026). Cycle-Informed Triaxial Sensor for Smart and Sustainable Manufacturing. IEEE Transactions on Industrial Informatics, 22(4), 2156–2165. https://doi.org/10.1109/TII.2026.3541236

[7] Chen, W., & Gao, X. (2025). Automatic control technology of mechanical equipment based on microelectronic sensor signal control. Frontiers in Mechanical Engineering, 11, 1557863. https://doi.org/10.3389/fmech.2025.1557863

[8] Kumar, S., & Singh, R. (2025). IOT-Based Industrial Equipment Monitoring System for Mechanical Fault Diagnosis. Research in Signal and Information Systems, 10(2), 78–85.

[9] Huang, Z., & Liu, P. (2024). Improved Variational Mode Decomposition for Industrial Sensor Signal Denoising. Measurement Science and Technology, 35(8), 085103. https://doi.org/10.1088/1361-6501/ad52f9

[10] Sun, D., & Wang, Q. (2025). Integrating Intelligent Sensing and Ensemble Learning for Industrial Equipment Health Monitoring. Journal of Electronics and Information Technology, 47(10), 3120–3128.

[11] Lin, H., Jiang, Y., Xu, J., Xu, J. J., Lu, Y., Hu, Z., Chen, Y. C., & Wang, H. (2025). Graph-guided dual-level augmentation for 3D scene segmentation. In Proceedings of the 33rd ACM International Conference on Multimedia (pp. 8517–8526). ACM. https://doi.org/10.1145/3737173.3754321