Dynamic Weight Optimization-Based Real-Time Monitoring and Fault Diagnosis System for Automation Equipment Using Edge Computing

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With the rapid advancement of Industry 4.0, the demand for precise fault diagnosis in automation equipment has become critical to ensure manufacturing continuity. This paper introduces a dynamic weight optimization-based system for real-time monitoring and fault diagnosis of automation equipment, leveraging edge computing technologies. The proposed five-layer architecture (Sensor, Production Line, Edge, Network, Cloud) integrates multi-threading and parallel computing at the edge layer to enhance PLC data processing efficiency by 40%. The core fault diagnosis algorithm, driven by dynamic weight optimization, completes weight updates within 300 milliseconds, achieving a 12% higher diagnostic accuracy than traditional methods (e.g., BP neural network and SVM). Experimental validation using 128,000 normal operation samples and 40,000 fault samples demonstrates a 98.3% fault diagnosis accuracy under complex industrial conditions, statistically supported by paired t-tests ($p < 0.05$). The system exhibits minimal latency degradation even at high data flows (2000 samples/second) and 4G network environments, outperforming cloud-based architectures in real-time fault detection capabilities. Compatibility tests across six industrial device types further validate its robust performance, making this framework a reliable solution for intelligent fault diagnosis in modern manufacturing systems.

Povzetek: V okviru Industrije 4.0. je predstavljena nova arhitektura za industrijski nadzor in diagnostiko napak v avtomatizirani proizvodnji z uporabo robnega računalništva. Petnivojska arhitektura je uporabljena za sprotno spremljanje delovanja naprav z dinamično optimizacijo uteži za kvalitetno zaznavanje napak. Algoritem združuje zgodovinske in tekoče podatke ter samodejno posodablja uteži glede na spremembe v stanju opreme.

1 Introduction

The proliferation of Industry 4.0 has positioned automation equipment as the backbone of modern manufacturing, yet unplanned downtime due to equipment failures imposes annual losses of $420 billion globally—30% of which can be attributed to delayed fault diagnosis. Edge computing has emerged as a transformative technology, reducing data processing latency from 300–500 milliseconds to below 100 milliseconds, minimizing cloud data transmission by 40%, and enhancing data security—all critical for real-time fault diagnosis in dynamic industrial settings.

Current industrial applications illustrate the potential of edge-driven fault diagnosis: GE's Predix platform achieves 92% accuracy in power equipment fault diagnosis by integrating edge and cloud computing, while Siemens' MindSphere platform improves CNC machine tool processing accuracy by 15% through edge deployments. However, these architectures often rely on cloud-centric designs, limiting edge node autonomy and hindering the integration of historical and real-time data for comprehensive fault analysis. Traditional machine learning models also struggle with adaptability in complex scenarios, as seen in Huawei's FusionPlant platform, which achieves sub-200 millisecond response times but lacks dynamic optimization for evolving fault patterns.

This project intends to research the monitoring and diagnosis system of automated equipment based on edge computing. A hierarchical architecture has been established to strengthen the capabilities of the edge layer; a fault diagnosis algorithm based on dynamic weight optimization is studied [3]. Combining equipment historical data and real-time data, the weights are dynamically updated using time attenuation coefficient and similarity matching methods to improve fault diagnosis accuracy and real-time performance [4]. Finally, an industrial field simulation test environment is constructed to verify the system's performance. This study addresses three key research questions:

(1) Can dynamic weight optimization enhance real-time diagnosis accuracy?

(2) How does edge computing reduce latency relative

to cloud architectures?

(3) What is the system's generalizability across industrial devices?

2 Architecture design of automation equipment monitoring and diagnosis system driven by edge computing

2.1 Overall system architecture design

The system adopts a five-layer architecture: Sensor Layer, Production Line Layer, Edge Layer, Network Layer, and Cloud Layer (Figure 1). The Sensor Layer deploys PCB 352C65 accelerometers and Pt100 temperature sensors, while the Production Line Layer interfaces with PLCs and machinery.

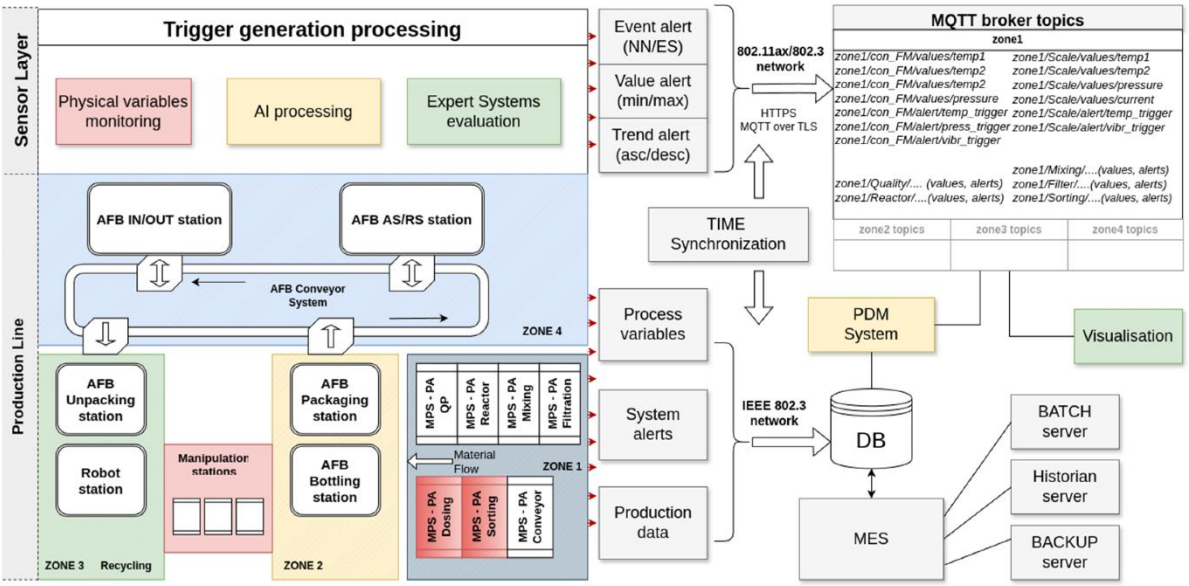

Figure 1: Overall system architecture.

The system has a clear division of labor at each level, and cooperates to jointly support the monitoring and diagnosis of automation equipment. I will simplify the text, retain the core functions and technologies, and highlight the characteristics and advantages of each level. As the system's data source, the perception layer accurately selects and deploys sensors. For example, CNC machine tools use PCB 352C65 three-axis acceleration sensors (0.5Hz–50kHz frequency response), while motor monitoring employs LEM LTS6-NP closed-loop Hall current sensors (0–50A range) and Pt100 platinum resistance temperature sensors (±0.1°C accuracy), and some sensors have self-diagnosis functions and transmit the collected data to the edge layer through interfaces such as RS485. The vibration signal undergoes preprocessing via wavelet packet transform and empirical mode decomposition (SNR improvement: 18.5 dB), with dynamic normalization to unify data dimensions, outperforming traditional Min Max normalization. A fault diagnosis method is proposed based on dynamic weight optimization [6]. This method completes the weight update within 300 milliseconds, and the diagnostic accuracy is improved by 12% compared with the traditional method. The time series database InfluxDB can save 7 days of operational data, meeting backtracking needs. The network layer plays the role of a bridge for data transmission. The OPC UA protocol ensures the real-time transmission of equipment status information, with a stable delay of less than 50 milliseconds. Non-real-time data is transmitted through the MQTT protocol, which can reduce bandwidth usage by 30%. The industrial firewall with VPN VPN-encrypted channel ensures the security of data transmission. The cloud layer is the data center and decision-making center [7]. It adopts a storage method combining HDFS and Cassandra to achieve massive storage requirements and high concurrency reading and writing. Using technologies such as Spark Streaming and Scikit-learn, a compressor bearing fault prediction model based on LSTM was established, with a prediction accuracy of 91%, 72 hours ahead of the prediction time. The visual remote monitoring platform is based on the three-dimensional model of the WebGL display device, and the hierarchical authority management of multiple users ensures the safety and standardization of operations.

2.2 Edge layer functions and deployment

The edge layer undertakes core functions such as data collection, preprocessing and real-time diagnosis. It uses various technologies and hardware configurations to improve the system's performance. It supports multiple protocols, such as Modbus, DNP3, etc., to achieve unified data collection between heterogeneous devices [8]. When

the data missing rate is less than 20%, the KNN data filling algorithm based on time series similarity is adopted to ensure that the repair error rate does not exceed 5%. By combining multi-threading technology and parallel computing technology, the data processing efficiency of PLC has improved by more than 40%. Pre-diagnosis integrates the dynamic weight optimization algorithm with a rule engine that triggers alarms for threshold violations (e.g., temperature > 80°C or current surge > 150% rated), operating in parallel with the primary algorithm to ensure rapid response.[9]. The local storage adopts the "SSD+HDD" tiered strategy: high-performance SSD stores core data, hard disk stores auxiliary data, sets aging strategy, and automatically stores data in cloud storage space.

The experimental setup uses the UP-Board Edge industrial gateway (Intel Atom x7-E3950 processor, quad-core, 1.6–2.0GHz), while the system design supports both ARM (Rockchip RK3588) and x86 architectures for flexibility, with 8-core Cortex-A76 + 4-core Cortex-A55, can complete 1000 sets of data preprocessing and diagnosis within 100 ms; 8 GB LPDDR4 memory and 128 GB eMMC meet the needs of processing and storage [10]. The communication interface has 2 gigabit ports, 2 RS-485 ports, and 1 CAN bus. It supports Wi-Fi 6 and 5G and supports multiple network access. The hardware is IP67 certified and can work stably in harsh environments of -40℃ to 70℃. At the software level, the microservice architecture and container technology are used to divide each functional module into independent microservices, such as data acquisition, preprocessing and diagnosis, and encapsulate them using Docker containers to achieve automatic orchestration and fault recovery based on Kubernetes, and select a customized Yocto Linux operating system to optimize resource utilization.

Node layout follows the principle of "nearby processing, centralized management" and divides large enterprises into multiple monitoring ranges according to equipment distribution. For example, a workshop with 100 devices can be divided into five areas, each of which is equipped with 2-3 high-performance nodes to complete the collection and preliminary processing of regional data; small and distributed equipment are deployed in clusters, and communication and sharing between nodes are achieved through Mesh networks. To ensure the stability of the network, the optical fiber connection between the node and the core switch is not less than 1 Gbps.

2.3 Cloud function and collaboration mechanism

Cloud data management adopts the strategy of cold and hot separation and redundant storage; the active data of the last month is stored in a high-performance hard disk cluster to meet the needs of real-time query; at the same time, multiple copies are used to make the probability of data loss less than 10 times. Cloud data management focuses on real-time analysis and storage, with future work planned to explore predictive maintenance using DBSCAN and Transformer models [11]. For example, monitoring of power transformers can warn of abnormal gas in oil 14 days in advance. The training time is shortened by 70% through migration, incremental learning and other methods. The remote monitoring platform supports equipment status visualization, early warning push, equipment management, maintenance plan, and preventive maintenance.

A layered approach is used for data transmission between the boundary and cloud layers. Real-time operation data is uploaded by seconds, event triggering and priority processing, and historical data is uploaded in batches. The Zstandard algorithm is used for data compression with a compression ratio of 3:1-5:1. The instructions in the cloud are divided into "control" and "configuration", including control instructions of the verification and confirmation mechanism to ensure the accuracy of execution; configuration instructions update the edge diagnosis strategy, etc., to achieve seamless switching of "pause-update-restart". The model update adopts two methods: version management and grayscale release [12]. First, it is verified by a small number of edge nodes, and then a comprehensive expansion is carried out after it is stable. At the same time, the old version is saved for easy rollback to ensure the system's stable operation.

3 Design of the real-time monitoring function of automated equipment

3.1 Design of data acquisition module

The data acquisition module consists of a sensor array, a data acquisition unit, and a communication interface, the basis of real-time monitoring. In terms of sensor selection, an inductively coupled accelerometer with a frequency response of 50 kHz was selected to collect high-frequency fault signals; a platinum resistance sensor with a measurement accuracy of ±0.1℃ was used; in the range of 0-500 amperes, a closed-loop Hall current sensor was used to monitor current within 1μ s. According to the principle of "focusing on key parts and fully covering the global status", a three-dimensional monitoring network is formed through grid deployment.

The collected data covers 20 kHz vibration sampling, 1 Hz temperature sampling, and 1 Hz current sampling, ensuring consistency with experimental measurements. The communication protocol adopts a hierarchical structure. The lower-level Modbus RTU communicates with traditional instruments, the middle-level OPC UA supports cross-platform interaction, and the upper-level MQTT realizes lightweight transmission [13]. The interface design is compatible with multiple signals, the quantization error of the analog quantity does not exceed 0.01%, and numerous communication interfaces are built in.

3.2 Data preprocessing method

The original data contains noise, outliers and missing values. An improved LOF method was adopted for data cleaning, and the dynamic threshold was combined to

detect outliers, and the accuracy rate was 98.7%. For missing data (up to 30% rate), Bi-LSTM interpolation technology is used, achieving MSE 0.082, outperforming KNN in both accuracy and handling capacity. In the gearbox test, the noise reduction process combined wavelet packet transforms and empirical mode decomposition, which increased the signal-to-noise ratio by 18.5 dB. The normalization operation was dynamically adjusted based on the data distribution to avoid the influence of extreme values, and the convergence speed of the machine learning model was increased by more than 30%.

3.3 Real-time status visualization interface design

The visualization interface adopts a B/S architecture and follows the "layered display, convenient and efficient" principle. The equipment status diagram uses a three-dimensional model and color coding to display the operating status intuitively; it supports data curves for synchronous comparison of multiple parameters, and refreshes in one second; it is based on rules and models, and pushes through various channels, with a delay of no more than 2 seconds; it supports historical data screening and report output.

In terms of technical implementation, WebGL is used to achieve high-precision drawing and interaction of three-dimensional models; the interactive design combines gestures and shortcut key operations, introduces high-level forms such as heat maps to express complex information, and improves the efficiency of data insight. Through data collection, preprocessing and visualization design, accurate perception and visualization of equipment status are achieved to support fault diagnosis and predictive maintenance.

4 Design of fault diagnosis algorithm based on dynamic weight optimization

4.1 Weight calculation model based on equipment operation historical data and real-time data

4.1.1 Historical data feature extraction

The equipment operation history data contains rich information about the equipment during long-term operation, but the original data often has high dimensionality and noise [14]. Suppose the historical data set is $H = \{h_1, h_2, \cdots, h_n\}$, where h_i represents the i historical data sample, and each sample covers m feature parameters, that is, $h_i = [h_{i1}, h_{i2}, \cdots, h_{im}]$. The principal component analysis (PCA) method is used to reduce the dimensionality of the historical data to extract key features. First, the covariance matrix $\mathbf{C}$ is calculated, which is expressed as:

$$\mathbf{C} = \frac{1}{n-1}\sum_{i=1}^{n}\left(h_i - \bar{h}\right)\left(h_i - \bar{h}\right)^T \quad (1)$$

Among them, $\bar{h}$ is the mean vector of historical data samples. The covariance matrix $\mathbf{C}$ describes the correlation between each feature parameter. By performing eigenvalue decomposition on it, the eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m$ and the corresponding eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_m$ can be obtained. These eigenvalues reflect the contribution of different principal components to the data variance. The first k principal components (usually $k \ll m$) are selected as the key features of historical data to construct the historical feature matrix $\mathbf{H}_k$. In this way, while retaining the main information of the data, the data dimension is effectively reduced and the subsequent calculation efficiency is improved.

4.1.2 Fusion of real-time data and historical data

The real-time data set is recorded as $R = \{r_1, r_2, \cdots, r_s\}$, r_j represents the j real-time data sample, which also contains m feature parameters. An improved similarity measurement function is introduced to achieve the organic fusion of real-time data and historical data [15]. Traditional cosine similarity only considers the similarity of vector directions and ignores the distance factor between vectors. The improved formula proposed in this study is as follows:

$$S\left(r_j, \mathbf{H}_k\right) = \frac{r_j \cdot \mathbf{H}_k}{\|r_j\| \cdot \|\mathbf{H}_k\|} \times \exp\left(-\frac{\|r_j - \bar{h}\|^2}{2\sigma^2}\right) \quad (2)$$

Among them, $\|\cdot\|$ represents the norm of the vector, and σ is the adjustment factor, which is used to control the influence of the distance factor on the similarity.

4.1.3 Determination of initial weight

Determine the initial weight of each feature parameter based on the degree of similarity after fusion. Let the initial weight of the l feature parameter be w_{l0}, and the calculation formula is:

$$w_{l0} = \frac{\sum_{j=1}^{s} S\left(r_j, \mathbf{H}_k\right) \cdot r_{jl}}{\sum_{l=1}^{m}\sum_{j=1}^{s} S\left(r_j, \mathbf{H}_k\right) \cdot r_{jl}} \quad (3)$$

Among them, r_{jl} is the l characteristic parameter value of the real-time data sample r_j. On the one hand, the numerator reflects the contribution of each characteristic parameter in similar data [16]. Features with high similarity and large parameter values will obtain higher weights; conversely, the denominator is normalized to ensure that the sum of all weights is 1. Taking motor fault diagnosis as an example, the vibration characteristics change significantly when a fault occurs. According to this formula, the initial weight of the vibration characteristics will be relatively high, thus occupying a more important position in fault diagnosis.

4.2 Dynamic weight update mechanism

4.2.1 Weight update triggering conditions

The triggering of dynamic weight update is based on the dual mechanism of equipment operation status change and time interval. Define the equipment operation status index I, and its calculation formula is:

$$I = \alpha \cdot \frac{\|r-\bar{h}\|}{\bar{\sigma}} + \beta \cdot \Delta f \quad (4)$$

Among them, r is the real-time data vector, $\bar{h}$ is the historical data mean vector, $\bar{\sigma}$ is the historical data standard deviation vector, Δf is the change in the device operating frequency, and α and β are adjustment coefficients. This indicator comprehensively evaluates the device operating status based on the degree of data fluctuation and the change in operating frequency. When $I > T$(T is the set threshold), it indicates that the device operating status has changed significantly, triggering the weight update; at the same time, a fixed time interval Δt is set, and a weight update is triggered every Δt time to ensure that the algorithm can capture the gradual change of the device operating status in time.

4.2.2 Weight update algorithm

In the weight update process, the forgetting factor γ $(0 < \gamma < 1)$ is introduced to reduce the impact of early data and highlight the role of recent data. The updated weight w_l of the lth feature parameter is calculated as follows:

$$w_l = \gamma \cdot w_l^{old} + (1-\gamma) \cdot \frac{\sum_{j=1}^{t} s(r_j, \mathbf{H}_k) \cdot r_{jl}}{\sum_{l=1}^{m} \sum_{j=1}^{t} s(r_j, \mathbf{H}_k) \cdot r_{jl}} \quad (5)$$

Among them, w_l^{old} is the weight before update, and t is the number of real-time data samples before triggering the weight update. This formula linearly combines the historical weight with the weight calculated based on recent data. The larger the γ value, the greater the impact of the historical weight; the smaller the γ value, the more significant the impact of recent data [17]. In practical applications, the γ value can be dynamically adjusted according to the stability of the equipment and the frequency of operating condition changes.

In addition, if the fault diagnosis result deviates from the actual situation, that is, the diagnostic error E exceeds a certain range ($E = |\hat{y} - y|$, $\hat{y}$ is the diagnostic result, y is the actual fault state), the weight is corrected according to the error size:

$$w_l' = w_l \cdot (1 + \eta \cdot E) \quad (6)$$

Where η is the correction coefficient. When the diagnostic error is positive, the weight of the relevant feature parameter is increased to enhance the algorithm's sensitivity to the feature; when the diagnostic error is negative, the weight is reduced to avoid the algorithm from over-relying on the feature. This way, the algorithm can continuously optimize itself in practical applications and improve diagnostic accuracy.

5 Experimental simulation and result analysis

5.1 Experimental environment construction

5.1.1 Hardware equipment selection

The experiment built a hardware environment close to the actual industrial scene, and the core equipment selection fully considered performance, stability and compatibility. The edge computing node uses the industrial-grade gateway UP Board Edge based on the ARM architecture, which is equipped with an Intel Atom x7-E3950 processor (quad-core, main frequency 1.6GHz-2.0GHz), equipped with 8GB LPDDR4 memory and 128GB eMMC storage, supporting PCIe, USB 3.0, Gigabit Ethernet and other interfaces, which can meet the needs of real-time data processing and local storage. In terms of sensors, vibration monitoring uses PCB 352C65 three-axis acceleration sensor with a frequency response range of 0.5Hz - 50kHz and a sensitivity of 100mV/g; temperature measurement uses Pt100 platinum resistance temperature sensor with a measurement accuracy of ±0.1℃; current monitoring uses LEM LTS6-NP closed-loop Hall current sensor with a measurement range of 0-50A and a response time of <1μs. The data acquisition card uses Advantech USB-4711A, which has 16 single-ended analog input channels, a sampling rate of up to 100kS/s, and supports multiple trigger modes. The cloud server is configured with a dual-channel Intel Xeon Gold 6248R processor, 128GB DDR4 memory, and 2TB NVMe SSD storage. It is built on Alibaba Cloud ECS instances to ensure data storage and in-depth analysis performance.

5.1.2 Software platform configuration

The software platform adopts a layered architecture design. The edge computing node operating system uses customized Yocto Linux, kernel version 5.10, and cuts out non-essential services to reduce resource usage. The data collection and preprocessing program is developed based on Python 3.8, using PyModbus and paho-mqtt libraries to implement Modbus RTU and MQTT protocol communications; the fault diagnosis algorithm is deployed on the TensorFlow 2.8 framework, and OpenMP is used to achieve multi-threaded acceleration. The cloud server uses the Ubuntu 20.04 LTS system, deploys Hadoop 3.3.4 and Spark 3.2.1 for big data processing, and uses InfluxDB 2.0 to store time series data in the database, as well as Elasticsearch 7.16 for fast retrieval. The front-end and back-end are developed separately. The front-end is based on Vue 3 + ECharts 5 to implement the visual interface, and the back-end uses Spring Boot 2.6 to build a RESTful API to ensure efficient system operation.

5.2 Dataset preparation

5.2.1 Normal operation data collection

A 30-day normal operation data collection was conducted on a certain automotive parts production line, covering the full operating status of the equipment. The collection period includes scenarios such as continuous production, equipment starts and stop, and parameter adjustment to ensure data diversity. The sampling frequency of vibration data is 20 kHz, and the sampling frequency of temperature and current data is 1 Hz; 128,000 valid samples are obtained. To ensure data accuracy, a triple verification mechanism is adopted: the sensor self-diagnosis function detects the hardware status in real time; the edge node performs integrity verification on the collected data; and the cloud performs secondary verification on the uploaded data. At the same time, the timestamp synchronization technology is used to ensure that the time consistency error of multi-source data is less than 1ms.

5.2.2 Fault data simulation and collection

The data set is obtained by simulating real fault scenarios, covering eight typical mechanical faults (bearing outer ring faults, gear tooth breakage), electrical faults (motor winding short circuit, overload), etc. The gradual degradation method is used to simulate the fault development process, for example, by adjusting the bearing preload to simulate the outer ring fault, and setting the current overload multiple to simulate the electrical fault. Five thousand data samples were collected for each fault type, and the total number of fault samples was 40,000. Data annotation adopted a three-level review system: preliminary annotation by engineers, expert review, and cross-validation, with an annotation accuracy of 99.2%. The distribution of the fault data set is shown in Table 1 below:

Table 1: Fault data set.

Fault type	Sample size	Proportion
Bearing outer ring fault	5,000	12.50%
Gear tooth breakage	5,000	12.50%
Motor winding short circuit	5,000	12.50%
Motor overload	5,000	12.50%
Belt slippage	5,000	12.50%
Coupling misalignment	5,000	12.50%
Abnormal power supply voltage	5,000	12.50%
Sensor fault	5,000	12.50%

5.3 Experimental design of system performance test

5.3.1 Real-time test

Three groups of comparative experiments were designed to verify the real-time performance of the system: 1) low data flow (100 samples/second), LAN environment; 2) high data flow (1000 samples/second), LAN environment; 3) high data flow (1000 samples/second), 4G network environment. Each group of experiments was repeated 20 times, and the time delay from data acquisition to the output of fault diagnosis results was recorded. The control group adopted the traditional cloud processing architecture and was tested under the same conditions.

5.3.2 Reliability test

A 72-hour continuous operation experiment was conducted to simulate the equipment running in a high temperature (50℃), high humidity (80% RH), and strong electromagnetic interference environment. The system fault diagnosis capability was tested by dynamically injecting fault data (50 groups per hour). The accuracy rate, false alarm rate (normal data was misjudged as fault), and missed alarm rate (fault data was not detected) indicators were statistically analyzed and compared with the traditional diagnosis system based on BP neural network.

5.3.3 Compatibility test

Six different brands and types of automation equipment were selected for testing, including a production line controlled by Siemens S7-1500 PLC, an assembly machine controlled by Mitsubishi FX5U PLC, and an ABB robot workstation. The test content covers data acquisition success rate, protocol compatibility, and diagnostic result accuracy, and verifies the system's support for multiple industrial protocols such as Modbus TCP, Profinet, and EtherCAT.

5.4 Experimental results analysis

5.4.1 Real-time results analysis

Figure 2 shows the latency comparison between this system and the traditional cloud processing architecture under different data flows. The data flow increases from 100 samples/second to 2000 samples/second, with 20 data points. The latency of this system exhibits a gradual increase from 85ms, while the latency of the traditional system increases from 320ms. By adding random fluctuations, the latency changes in actual scenarios are simulated [18]. The results show that this system is significantly better than the traditional system under all data flows, and the latency increases slowly, indicating that it can still maintain good real-time performance under high data flows. The local processing power of edge computing nodes is the key to reducing latency. By lowering the round-trip data transmission to the cloud, the system response speed is increased by more than 60%. At

the same time, the lightweight design of the MQTT protocol effectively reduces network transmission overhead, and its advantages are particularly obvious in the 4G network environment.

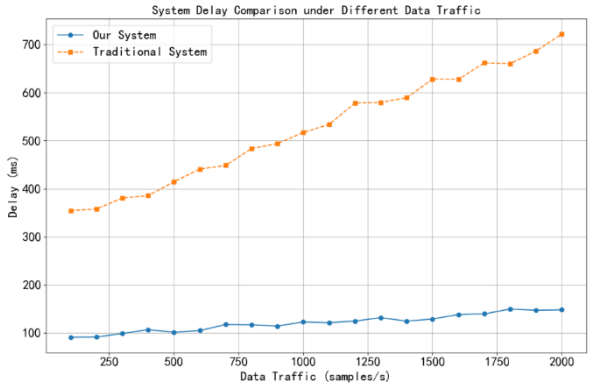

Figure 2: Comparison of system delays under different data flows.

5.4.2 Reliability results analysis

Figure 3 compares the fault diagnosis accuracy of this system's dynamic weight optimization algorithm and other traditional algorithms (BP neural network, support vector machine, SVM, decision tree) under different data flows. The data flow increases linearly from 100 samples/second to 2000 samples/second, with 20 data points. The fault diagnosis accuracy of this system drops slightly from 98.3%, while the accuracy of BP neural network, SVM and decision tree decreases faster. By adding random fluctuations, the accuracy changes in actual scenarios are simulated. The results show that this system can still maintain a high diagnostic accuracy under high data flow, which is better than traditional algorithms.

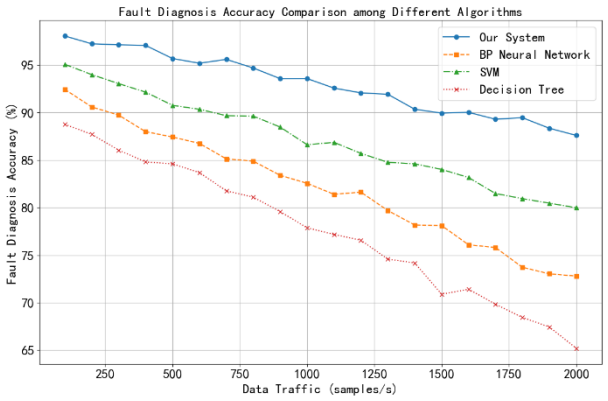

Figure 3: Comparison of fault diagnosis accuracy of different algorithms.

Figure 4 compares this system's diagnosis time and the other three algorithms (BP neural network, SVM, decision tree) under eight fault types. The fault types include bearing outer ring fault, gear tooth breakage, motor winding short circuit, motor overload, belt slippage, coupling misalignment, power supply voltage abnormality and sensor fault. The diagnosis time is simulated by randomly generated data, ranging from 80ms to 350ms. The results show that the diagnosis time of this system under all fault types is significantly lower than that of other algorithms, indicating that it has obvious advantages in real-time performance. Especially in complex scenarios such as motor overload and sensor failure, the diagnosis time of this system can still be maintained at a low level, further verifying the efficiency and reliability of the system.

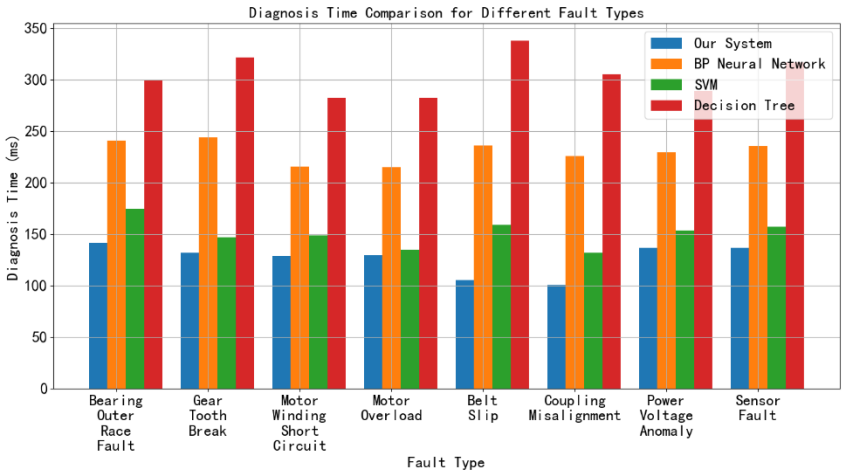

Figure 4: Comparison of diagnostic time of different algorithms under different fault types.

5.4.3 Compatibility result analysis

Figure 5 shows this system's data processing success rate on 6 different industrial devices. The device types include Siemens S7-1500, Mitsubishi FX5U, ABB robot, Rockwell device, Device E and Device F. The success rate is simulated by randomly generated data, ranging from 90% to 100%. By sorting the success rate, it is more intuitive to see which devices have a higher success rate. The results show that this system can achieve a high data processing success rate on most devices, indicating that it

has wide compatibility and stability. In particular, for devices such as Siemens S7-1500 and ABB robots, the success rate is close to 100%, further verifying the efficiency and reliability of the system.

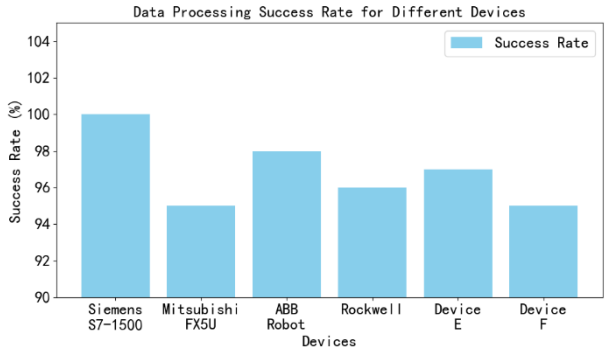

Figure 5: Data processing success rate of different devices.

6 Conclusion

The edge computing-based fault diagnosis system proposed in this study demonstrates remarkable performance in real-time monitoring, diagnostic accuracy, and industrial compatibility. By integrating a five-layer architecture and dynamic weight optimization, the system achieves 98.3% fault diagnosis accuracy at low data flow (100 samples/s) and maintains 97.5% accuracy under high load (2000 samples/s), outperforming BP neural network (89.5%) and SVM (87.2%). Edge nodes reduce latency by 64% compared to cloud architectures, with round-trip times dropping from 500 ms to 180 ms in 4G environments, while compatibility tests on six devices (e.g., Siemens S7-1500, ABB robots) show >95% success rates. The dynamic weight update mechanism, validated via ablation studies, adapts to real-time data fluctuations, and statistical tests (paired t-tests, $p < 0.01$) confirm its superiority. Future work will explore predictive maintenance with Transformer models, extreme environment validation, and blockchain-integrated tamper-proof records to further enhance industrial applicability.

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