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Design of Equipment Online Monitoring and Fault Diagnosis Platform Based on IOT

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Design of Equipment Online Monitoring and Fault Diagnosis Platform Based on IOT

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Abstract. Complex equipment in the process industry is the core productivity of automated manufacturing. Fault prediction, diagnosis, and health maintenance of such equipment are important factors to ensure continuous and reliable operation of production. However, how to adjust the fault judgment rules in time according to the changes in the operating conditions and process of the equipment is the core design content of the fault diagnosis platform. The platform of this paper presented is mainly based on stress wave condition monitoring technology, which combined with process monitoring to form an online monitoring data set of the equipment; Then use the data fusion technology to fuse the collected signals at the decision-making level, and finally combine principal component analysis and the BP neural network to predict the equipment's health trend and fault type.

1. Introduction

Complex equipment in the process industry serves as the company's core assets and profit source, and effective management and maintenance of equipment is an important means of protecting corporate assets. In today's information-intensive infiltration, it is imperative to properly implement equipment online monitoring and fault diagnosis. The stress wave monitoring technology can directly reflect the working state, expected fault and life cycle of the mechanical equipment in continuous operation. In addition, process monitoring parameters such as pressure, temperature, and current can also be used for fault diagnosis of mechanical equipment. At present, the industry divides fault diagnosis methods into three categories: Fault diagnosis based on analysis model, empirical knowledge and data driven [1].

Fault diagnosis method based on analysis model is a method that combines a mathematical model and the current operating status of the equipment. The results of this kind of fault diagnosis method are more accurate, but it is very difficult to establish accurate models, or even impossible [2].

Fault diagnosis method based on empirical knowledge is a method that combines the experience of domain experts and the actual operation of the equipment to diagnose. The accuracy of this type of fault diagnosis method depends on the correctness of the knowledge source and the reliability of the reasoning mechanism. Expert system [3, 4] is the typical representative.

The data-driven fault diagnosis method is aimed at complex equipment and uses a large amount of historical monitoring data for diagnosis. This type of diagnostic method avoids complicated mathematical models and expert experience, but the completeness and comprehensiveness of monitoring data are the main factors affecting the credibility of diagnostic results [5-11].

The IOT-based equipment online monitoring and fault diagnosis platform emphasizes equipment multiple condition perception, real-time online monitoring of data and intelligent fault diagnosis, and establishes technical support for active maintenance of various complex equipment in the process industry. The main monitoring method of this platform is high-frequency ultrasonic sensing technology--stress wave, which can collect real-time electronic signals of friction, impact and dynamic load of operating equipment, and filter out vibration and background audible noise, Then the platform combines with the process monitoring and manage process data, uses data fusion technology combined with principal component analysis (PCA) with dimensionality reduction capabilities to eliminate noise and redundant features, prevents overfitting, and finally uses BP neural network algorithms for fault diagnosis.

2. Methodology

2.1. IOT

The Internet of Things (IOT) is a ubiquitous network built on the Internet. It uses sensors such as local area networks or the Internet to connect sensors, controllers, machines, people, and things to form a connection between people and things, things and things, to achieve remote management control and intelligent network, but its important foundation and core is still the Internet. It is integrated with the Internet through various wired and wireless networks to deliver real-time and accurate information to the target source.

The platform adopts IOT technology to achieve the following functions:

- Provide reliable transmission, storage, and convenient scalability, and use cluster backup for historical data of various types of monitoring.
- Bind the identification ID and APP Key to complete the link between the equipment and the cloud storage, the data communication between the web server and the upper-layer application, and provide API interfaces for the upper-layer SaaS (Software as a Service) application or third-party system.
- Upload application data with timestamps and adapt the communication protocol engine according to the scenario, such as the protocol of HTTPs, MQTT, CoAP.
- Provide rich graphical human-computer interaction interface and background management.

2.2. Equipment Monitoring

Online monitoring is the continuous or regular monitoring of the working status of the equipment or its components, and the monitoring results are automatically uploaded to the terminal.

Stress wave is a kind of ultrasonic energy pulse, which is transmitted by the friction, mechanical shock and dynamic load transmitted by the operating equipment components in all directions to conduct ultrasonic energy (stress wave energy, SWE) [12]. Under the premise of undamaging the body of the equipment, changes in the stress wave caused by changes in the working state of the components can be monitored on the surface of the exterior of the equipment such as bearings, gear boxes and other components. Therefore, by monitoring the stress wave, you can find the earliest signs of failure of the component, and then start to diagnose the failure. In the traditional P-F curve index, the time response of the stress wave technology to the fault trend is shown in figure 1, which depicts the process of equipment degradation.

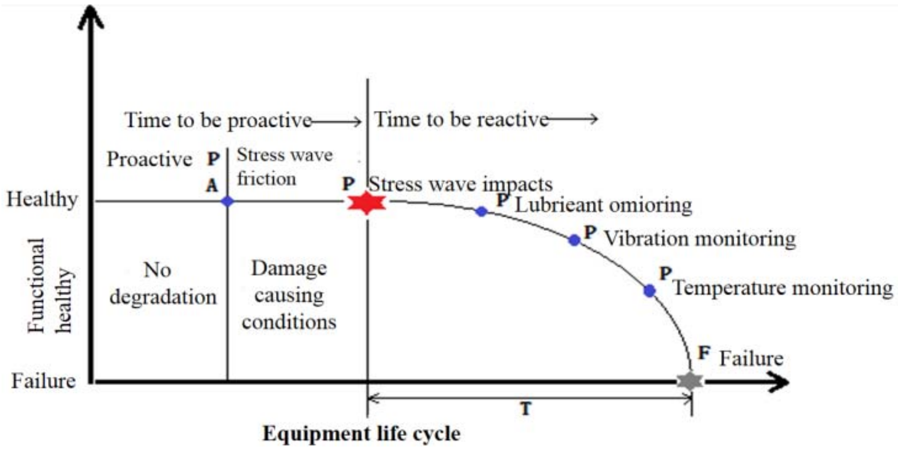

Figure 1. Response point of stress wave technology during equipment degradation cycle

In figure 1, point A is the initial occurrence of the early failure of the equipment; point P is the early failure point that can be detected; point F is the functional failure point of the equipment; T is the time period during which the equipment develops from early failure to functional failure, which is called the P-F interval [13].

2.3. Data Fusion

Data fusion technology refers to information processing technology that uses a computer to automatically analyze and comprehensively process certain monitoring information obtained under certain criteria to complete the required decision-making and evaluation tasks.

With the increasing complexity of the system, relying on a single sensor to monitor physical quantities is obviously more restrictive. Therefore, multi-sensor technology is used in the fault diagnosis system to monitor multiple characteristic quantities (such as stress waves, temperature, pressure, flow, etc.), and the information of these sensors is fused to improve the accuracy and reliability of equipment fault diagnosis. This article uses data fusion to reasonably integrate the information detected by multiple sensors with third-party monitoring systems, such as DCS, PLC, etc., through artificial intelligence algorithms and related rules to improve the accuracy and intelligence of condition monitoring and fault diagnosis.

There are three types of data fusion technologies in the field of current equipment fault diagnosis:

2.3.1. Original data layer fusion. Data fusion and analysis are performed before the original monitoring data of various sensors are preprocessed. Data layer fusion generally adopts a centralized fusion system for fusion processing. For example, the process of confirming target attributes by performing image processing on a blurred image containing a certain pixel in an imaging sensor belongs to data-level fusion.

2.3.2. Feature layer fusion. Feature layer fusion is a middle-level fusion. It first performs feature extraction on the original information from the sensor (features can be the edge, direction, speed, etc. of the target), and then comprehensively analyzes and processes the feature information. The advantage of feature layer fusion is that it realizes considerable information compression, which is conducive to real-time processing. Because the extracted features are directly related to decision analysis, the fusion result can give the maximum feature information required for decision analysis. Feature layer fusion generally adopts a distributed or centralized fusion system. Feature layer fusion can be divided into two categories: one is target condition fusion; the other is target feature fusion.

2.3.3. Decision layer fusion. The decision layer fusion observes the same target through different types of sensors, and each sensor completes the basic processing locally, including preprocessing, feature extraction, recognition or judgment, to establish a preliminary conclusion on the observed target. Then, the decision-level fusion decision is made through association processing, and finally the joint inference result is obtained. This is also the data fusion method adopted by this platform. The fusion process is shown in figure 2.

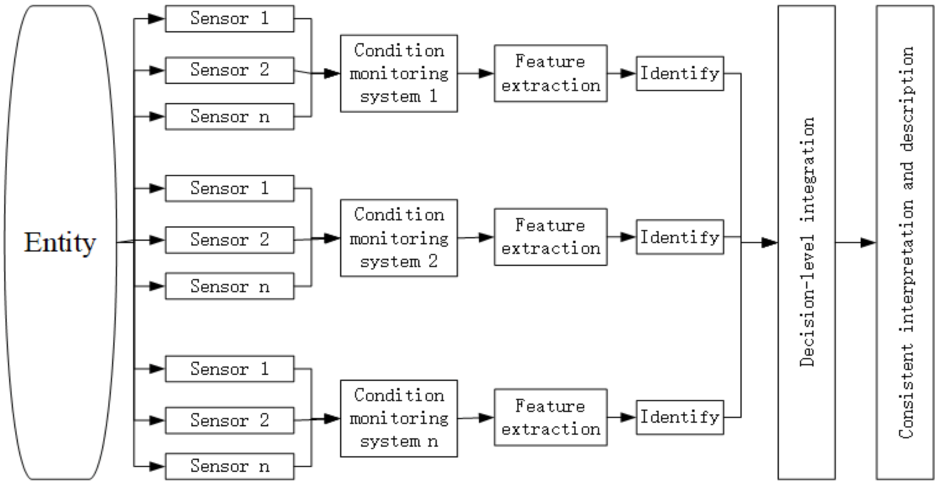

Figure 2. Decision layer fusion process

2.4. Fault Diagnosis

2.4.1. Principal component analysis. Principal component analysis is a method that uses the idea of dimensionality reduction to convert multiple indicators into several comprehensive indicators with little information loss. Random vector $X=(X_1,X_2,\cdots,X_p)'$ the mean of X is represented by μ, and the covariance matrix is represented by Σ. X changes linearly, that is, the original variable is transformed into a new comprehensive variable through a linear change. The transformation method is shown in equation (1):

$$\begin{cases} Y_1=u_{11}X_1+u_{12}X_2+\cdots+u_{1p}X_p \\ Y_2=u_{21}X_1+u_{22}X_2+\cdots+u_{2p}X_p \\ \cdots \\ Y_p=u_{p1}X_1+u_{p2}X_2+\cdots+u_{pp}X_p \end{cases} \tag{1}$$

Due to any linear change in formula (1), different Y can be obtained. Therefore, for better results, we want the variance of Y to be as large as possible and independent of each other. Therefore, there is a need for constraints when making linear changes. The constraint principles are as follows:

- $u_i'u_i=1$, that is $u_{i1}^2+u_{i2}^2+\cdots+u_{ip}^2=1(i=1,2,\cdots,p)$.
- Y_i and Y_j are independent of each other ($i\neq j$; i, $j=1,2,\cdots,p$).
- Y_1 is the linear combination with the largest variance when $X_1,X_2,\cdots,X_p$ satisfies principle 1. Y_2 has the largest variance under the premise that it is not related to the linearity of Y_1, and so on[14].

Based on the above three principles, the comprehensive variable $Y_1,Y_2,\cdots,Y_p$ is called the first, second, $\cdots$, P - th principal components of the original variable.

Normalize the collected stress wave energy values, DR sets, and vibration monitoring data, and calculate their correlation matrix. Then, the feature root of the correlation matrix and the feature vector corresponding to the feature root are solved. Finally, the top M principal components which cumulative contribution rate reaches 85% are selected.

2.4.2. BP neural network. BP neural network is a multi-layer feed forward neural network trained by an error back propagation algorithm. It determines the direction of parameter modification by calculating the gradient, and adjusts the calculation method of weights. The learning process consists of two steps. Step 1: Forward propagation of input information. Step 2: Back propagation of error terms. And each layer of neurons only affects the corresponding neurons of the next layer. Given a training data set: $D=\{(x_1,y_1),(x_2,y_2),\cdots,(x_m,y_m)\}$, $x_i \in R^d$, $y_i \in R^l$ that is, there are d attributes of the input, and the dimension of the output is l [15].

It is assumed that the activation function used by both the hidden layer and the output layer is a Sigmoid function. At the same time, for the training data set, the network output value $\hat{y}_k=\left(\hat{y}_1^k,\hat{y}_2^k,\cdots,\hat{y}_l^k\right)$ is assumed, that is,

$$\hat{y}_j^k = f\left(\beta_j-\theta_j\right) \tag{2}$$

The θ_j represents the corresponding bias value of the j-th neuron in the output layer. The β_j represents the input of the j-th neuron in the output layer of the network. $\beta_j=\sum_{h=1}^{q} w_{hj} b_h$, w_{hj} represents the mutual weight between the h-th neuron in the hidden layer and the j-th neuron in the output layer, and b_h represents the output of the h-th neuron in the hidden layer. Let E_k represent the mean square error of the network on (x_k,y_k), and the expression is as shown in equation (3):

$$E_k=\frac{1}{2}\sum_{j=1}^{l}\left(\hat{y}_j^k-y_j^k\right)^2 \tag{3}$$

Given the learning rate η, the update amount of the weight can be obtained.

$$\Delta w_{hj}=-\eta\frac{\partial E_k}{\partial w_{hj}} \tag{4}$$

According to the chain-derivation rule, equation (5) can be obtained.

$$\frac{\partial E_k}{\partial w_{hj}}=\frac{\partial E_k}{\partial \hat{y}_j^k}\cdot\frac{\partial \hat{y}_j^k}{\partial \beta_j}\cdot\frac{\partial \beta_j}{\partial w_{hj}} \tag{5}$$

According to the definition of β_j, Equation (6) can be obtained.

$$\frac{\partial \beta_j}{\partial w_{hj}}=b_h \tag{6}$$

The derivative of the Sigmoid function is shown in Equation (7):

$$f(x)'=f(x)\left(1-f(x)\right) \tag{7}$$

According to equations (2) and (3), the gradient term of the output layer neuron can be obtained as follows.

$$
\begin{aligned}
g_i &= -\frac{\partial Ek}{\partial \hat{y}_j^k} \cdot \frac{\partial \hat{y}_j^k}{\partial \beta_j} \\
&= -(\hat{y}_j^k - y_j^k)\, f(\beta_j - \theta_j)' \\
&= \hat{y}_j^k (1 - \hat{y}_j^k)\, f(y_j^k - \hat{y}_j^k)
\end{aligned} \tag{8}
$$

w_{hj} update methods available from equations (4), (5), (6), and (8).

$$\Delta w_{hj} = \eta g_i b_h \tag{9}$$

Similarly available

$$\Delta \theta_j = \text{-}\eta g_i \tag{10}$$

$$\Delta v_{ih} = \eta e_h x_i \tag{11}$$

$$\Delta \gamma_h = \text{-}\eta e_h \tag{12}$$

In equations (11) and (12):

$$
\begin{aligned}
e_h &= -\frac{\partial E_k}{\partial b_h} \cdot \frac{\partial b_h}{\partial \alpha_h} \\
&= -\sum_{j=1}^{l} \frac{\partial E_k}{\partial \beta_j} \cdot \frac{\partial \beta_j}{\partial b_h} f(\partial_h - \gamma_h)' \\
&= \sum_{j=1}^{l} w_{hj} g_j f(\partial_h - \gamma_h)' \\
&= b_h (1 - b_h) \sum_{j=1}^{l} w_{hj} g_j
\end{aligned} \tag{13}
$$

The specific steps as follows: Bringing the M comprehensive variables and their labels after the dimensionality reduction through the principal component into the BP neural network. First, the threshold and connection weight in the neural network are initialized, and the range of its random initialization value is (0, 1). Then step through steps 1 to 4 continuously until it stops when the given conditions are met.

Step 1: Calculate the sample output value based on the existing input layer and hidden layer connection weights and the output layer and hidden layer thresholds.
Step 2: Calculate the gradient of neurons in the output layer.
Step 3: Calculate the gradient of hidden layer neurons.
Step 4: Update the connection weights of the input and hidden layers and the thresholds of the output and hidden layers.

Finally, the neural network connecting the weights and thresholds is output. In summary, the monitoring data set of the equipment to be diagnosed is processed by principal component and then brought into the trained neural network, and the corresponding fault types are finally output through the neural network.

3. Platform Architecture

According to the background of the construction of equipment monitoring and equipment management informatization in the process industry, the architecture of the IOT-based equipment condition monitoring and fault diagnosis platform described in this article is shown in figure 3:

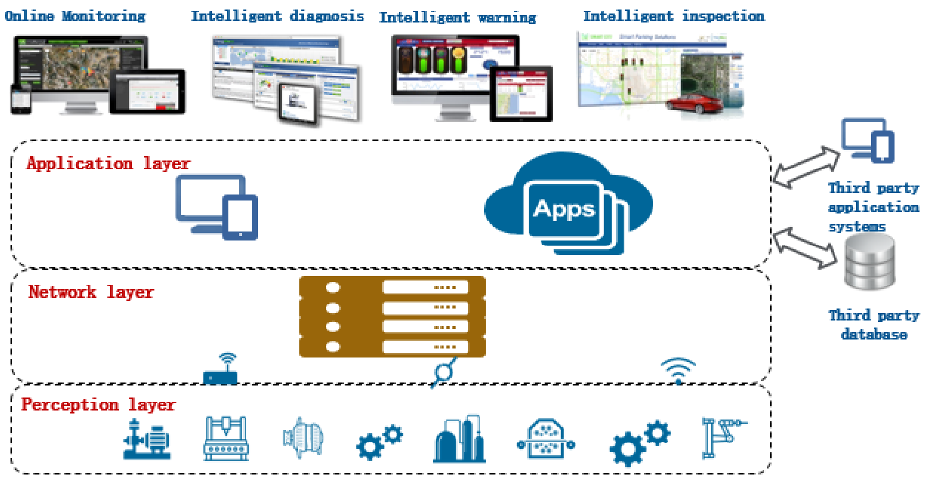

Figure 3. Architecture of the IOT-based equipment condition monitoring and fault diagnosis platform

According to the architecture described above, the platform includes the following seven functional modules from the bottom to the top:

Data acquisition module: Collect the operating signal of the equipment through various sensors in the field, conduct preliminary processing of the signal and transmit it to the data processing module.

Data processing module: The data collected from the data acquisition module is subjected to pre-processing, cleaning, feature extraction and other analysis and processing, so that the data meet the requirements for subsequent use.

Condition monitoring module: Based on monitoring technology and equipment characteristics, set monitoring rules or algorithms to compare data characteristic values or thresholds , and preliminarily judge whether the equipment has faults; If the fault is judged, the text warning, SMS warning or WeChat warning message push will be started simultaneously .

Equipment management module: access or manually enter the basic information of equipment, key components and core parameters of components from the third-party systems, and provide detailed auxiliary data for further fault diagnosis, such as bearing type of equipment, rated speed, etc.

Fault diagnosis module: if the fault of the equipment is preliminarily judged, the fault diagnosis shall be carried out to determine the fault type and location.

Decision support module: According to the results of equipment fault diagnosis and prediction, propose reasonable operation and maintenance measures.

Visualization module: Human-computer interaction interface, which presents the real-time value, location and basic information of equipment monitoring; And it presents diagnostic results, operation and maintenance measures recommendations for equipment that predicts faults.

4. Platform Functions

Based on the above seven functional modules, the functions of the equipment online monitoring and fault diagnosis platform based on IOT are mainly as follows:

4.1. Online Monitoring

Monitoring for equipment health or life cycle can be divided into three categories: equipment condition monitoring, process parameter monitoring and management process monitoring. Monitoring methods include direct-connected wired or wireless sensors, PLC (Programmable Logic Controller), DCS (Distributed Control System), and MES (Manufacturing Execution System) [16]. This platform uses the IOT technology to integrate, store, analyse, and visualize these three types of monitoring data as needed, as shown in figure 4.

4.1.1. Condition monitoring. One of the core of the equipment online monitoring and fault diagnosis platform based on IOT is equipment condition monitoring. At present, there are methods such as stress wave monitoring, vibration monitoring, infrared thermal imaging, oil monitoring and electrical monitoring; Stress wave monitoring and vibration monitoring have results Intuitive, real-time, and wide coverage of fault types. Infrared thermal imaging, oil monitoring, electrical diagnosis, etc. can be used as a supplement to the above two monitoring methods.

4.1.2. Process monitoring. The production process monitoring system, such as DCS, PLC, MES, can monitor the equipment's load operation pressure, temperature, flow, speed and other condition values in real time to determine the health of the equipment. In the precise troubleshooting of equipment faults, it is also possible to form closed loops through adjustment and monitoring of process parameters to improve equipment fault location.

4.1.3. Management process monitoring. Management process monitoring, equipment condition monitoring, and process monitoring belong to different branches of equipment management. And there is a deep intersection between the three methods. Based on the two monitoring methods mentioned above, the system involved can obtain equipment key component information, equipment online time, the running time, the last time the cause of the problem, the last fault time, maintenance time, maintenance content, etc., as monitoring the content of the management process, and these contents can be used as auxiliary information of equipment fault, fault diagnosis is predicted.

Figure 4. Equipment online monitoring

4.2. Fault Diagnosis

Equipment failure refers to an event or phenomenon in which it loses or reduces its specified function. It is manifested as abnormal production operation, some components of the equipment lose their original accuracy or performance, which makes it unable to operate normally and reduces the performance of technical. All of that causes production interruption or reduced efficiency affects production.

This platform is based on the definition of equipment failure. The reliability is mainly based on stress wave monitoring technology and supplemented by vibration monitoring technology. It also diagnoses equipment failure in combination with production process parameter monitoring, because early fault prediction or fault prediction is a more advanced maintenance guarantee method than fault diagnosis [5]. The work flow of equipment fault diagnosis is: multi-condition data collection, multi-condition feature extraction, data comparison, data fusion, fault diagnosis, enhanced diagnosis, and fault prediction. The process is shown in figure 5. The platform uses data fusion to reduce fault diagnosis and prediction errors and improve the confidence of fault diagnosis. Facing the situation of multiple monitoring information sources, multiple types of parameters, and multiple sensor information, the decision layer fusion method is used to diagnose the fault. Commonly the fused algorithms are neural networks, expert systems, fuzzy logic, Bayesian algorithms, Kalman filtering, etc. [17].

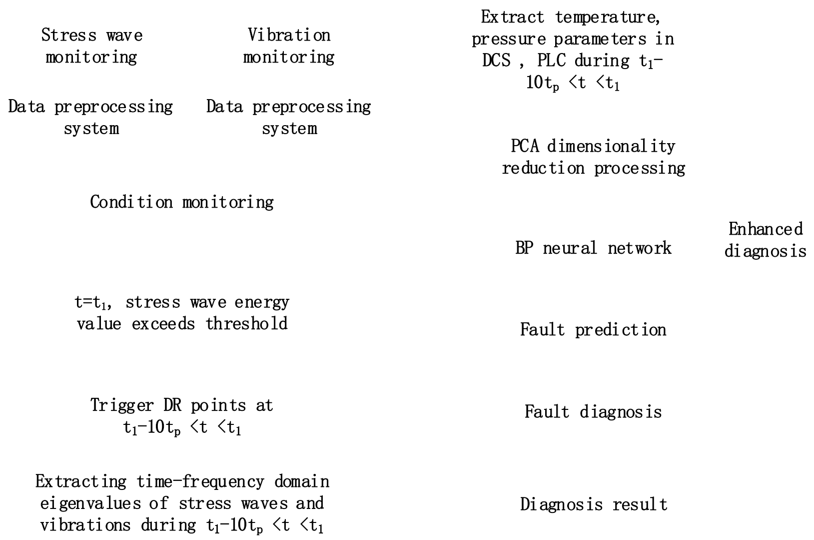

Figure 5. Intelligent fault diagnosis process

Definition of intelligent fault diagnosis process:

DR: Digital Record, which conclude FFT spectrum and histogram data set for analyzing friction and shock events.

t_1: The moment when the stress wave energy exceeds the set alarm threshold.

t_p: The sampling period of DR and the sampling period of vibration. The value of t_p may be different in different systems.

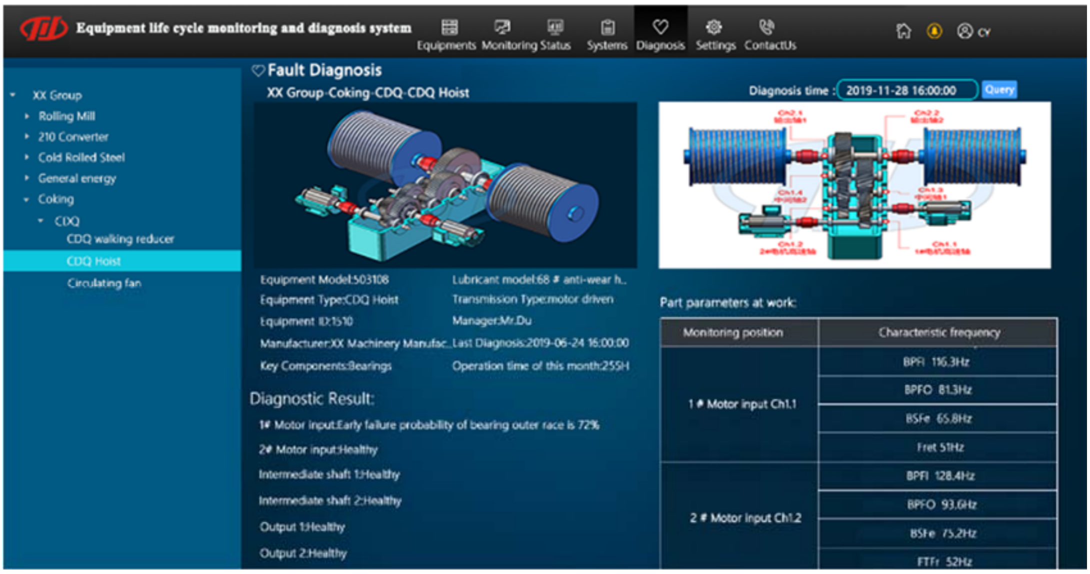

Figure 6. Equipment intelligent diagnosis

The initial fault judgment of this platform is completed by the stress wave monitoring system. The stress wave energy at a monitoring point of the equipment exceeds the fault alarm threshold is the initial fault judgment point. And this time is t1, when the intelligent diagnosis process is started. The platform extracts the condition data in t_1-$10t_p$ <t <t_1, the data are stress wave energy value, DR set and the original vibration monitoring data; Next, the stress wave energy value, DR set and the vibration monitoring raw data of each monitoring point are used as input of the principal component analysis. In order to eliminate the stress wave energy value, DR point and the characteristic value of the strong correlation of the vibration monitoring signal, that is to reduce the dimensionality of the collected signal, while avoiding over fitting. Then the results of the principal component analysis are used as the input parameters of the BP neural network to predict and diagnose the fault. Finally, the management process data of the production side is used as a means of enhancing diagnosis to improve the accuracy of fault location. A case of final intelligent diagnosis results is showing in figure 6.

4.3. Equipment Archives

Establish a sound mechanism for intelligent fault diagnosis diagnostic equipment and get highly accurate results, is inseparable from the equipment archives. Equipment archives are documents, records formed during the whole process of equipment from planning, design, manufacturing, installation, commissioning, use, maintenance, transformation, update to scrap. They are an important part of enterprise archives, as well as important part of equipment management. The normal operation, fault removal and maintenance are the basic tasks of equipment management, and equipment archive management provides basic technical.

Figure 7. Equipment Archives

As the main content of the management process monitoring, the equipment archive content of this platform includes: equipment name, equipment operating conditions, key component information, transmission mode, last diagnosis time, last failure time, last failure type, working temperature, etc. Those failure Parameters related to intelligent diagnosis. The equipment archive application case is shown in figure 7.

5. Conclusion

The technologies implemented by the IOT-based equipment online monitoring and fault diagnosis platform are mainly focused on data collection and convergence, online monitoring and stress wave technology, BP neural network and principal component analysis algorithms. Although the current field application has achieved certain results, the follow-up work of this platform is still heavy. The most urgent thing is to further improve the equipment file module, increase equipment inspection, equipment maintenance, and equipment maintenance, and use correlation analysis to extract the parameters in the newly added module and the parameters with strong correlation of equipment fault characteristic values to improve fault intelligence Confidence in diagnosis.

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