Research on Electrical Equipment Status Monitoring Method Based on Wireless Communication Technology

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Abstract. The current methods for monitoring the status of electrical equipment are prone to interference from the external environment, resulting in low accuracy of monitoring results and longer monitoring time. Therefore, this study proposes a method for monitoring the status of electrical equipment based on wireless communication technology. Firstly, a low-power wireless transceiver module is established based on RF transceivers. After selecting a suitable wireless communication receiving device, a wireless monitoring framework is established. Then, Fourier transform technology is used to collect electrical equipment status monitoring signal data, and wavelet analysis technology is used to organize the collected signals. Finally, neural network technology is used to evaluate the real-time status of electrical equipment. Through data mining, conduct in-depth analysis of signal data to obtain the final monitoring results. The experimental results show that this method can effectively improve the accuracy of monitoring results and shorten the output time of monitoring results.

Keywords: Wireless communication technology · Electrical equipment · Status monitoring · Fourier transform

1 Introduction

With the continuous rise of the country's overall economic level, the power industry (especially the power generation enterprises) develops rapidly, showing an unparalleled prosperity. On the one hand, the rapid growth of electricity consumption makes the power system network increasingly large, the number of electrical equipment used is increasing, forming a unified organic whole in the process of power production, transmission and use, which is conducive to improving the efficiency of the system. On the other hand, the unsafe factors affecting the safe operation of the power system have also increased sharply. Any major failure or failure of the electrical equipment in the system will have a chain effect of system collapse, resulting in human casualties and huge economic losses, affecting the harmony and stability of the society. Therefore, ensuring the safe and healthy operation of electrical equipment has become the focus of power system workers [1–3].

L. Yun et al. (Eds.): ADHIP 2023, LNICST 548, pp. 264–276, 2024.
https://doi.org/10.1007/978-3-031-50546-1_18

Electrical equipment failure refers to the abnormal working conditions of the power system, partial functional failure of electrical equipment, or the performance indicators of electrical equipment exceeding its rated range, usually resulting in electrical equipment entering a fault state. The structure of electrical equipment is complex, and the system is prone to malfunctions during operation. The main cause of failure refers to the physical, chemical, biological or mechanical processes that cause the failure of electrical equipment under operating conditions, such as corrosion, creep, wear, heating, aging, etc. [4]. With the rise and development of science and technology such as microprocessors and new anti-interference transmission, the research on online status monitoring of power equipment has gradually deepened. The research on dissolved gas systems, online monitoring of partial discharge and leakage of human mouth power generation equipment, and other equipment has successfully enabled real-time monitoring of experiments that could only be conducted through equipment debugging, providing the possibility for online management of equipment status.

With the development of infrared and optical fiber technology, the research of on-line condition monitoring is gradually carried out. Online condition monitoring overcomes the drawbacks of regular maintenance, carries on the condition assessment of electrical equipment, and then carries on the necessary maintenance of electrical equipment on the premise and basis of the condition assessment, avoids the waste of human and financial resources, and effectively guarantees the reliability of power supply. The state assessment of electrical equipment needs to make comprehensive use of all state information such as operating conditions, temperature and electromagnetic, etc. The principle is to process, classify and evaluate the collected state information of the equipment, and the later maintenance of the equipment is based on this technical support [5, 6]. In the state assessment, the fault prediction and alarm of electrical equipment is the most widely used.

At present, there are a lot of problems in condition monitoring methods of electrical equipment, and it is urgent to optimize and perfect them. Therefore, a method of electrical equipment condition monitoring based on wireless communication technology is proposed in this study. On the basis of the current method, the work cost is saved, the service life of the equipment is extended, and the reliability of the power system is greatly improved. This method achieves signal data acquisition and organization through the use of Fourier transform technology and wavelet analysis technology, fundamentally improving data quality, improving the accuracy of later monitoring results, and shortening monitoring time by effectively avoiding environmental interference.

2 Construction of Wireless Communication Electrical Equipment Monitoring Framework

The communication system is an important component of the power system. In recent years, with the continuous deepening of China's power system informatization construction, the power communication network has preliminarily formed. At present, various and fully functional communication methods such as microwave, power line carrier, optical fiber, and wireless mobile communication have been formed, playing a huge role in power load management, distribution automation, and power system status monitoring.

With the continuous development of the wireless communication industry and breakthroughs in second and third generation wireless communication technologies, more and more wireless communication technologies are being applied to power system communication, and wireless communication is also playing an increasingly important role in power communication [7]. Compared to various wireless communication methods, wireless radio frequency technology was selected in this study to construct a wireless communication electrical equipment monitoring framework.

The wireless data transmission module (RF transceiver) adopted in this study is a micro-power wireless transceiver module, which has the following characteristics: Receive and transmit in one, the working frequency is the international unified data transmission frequency of 433 MHz, FSK modulation, low transmission power, strong anti-interference ability, transmission range up to 450 m, suitable for the communication within the substation and other short distance power equipment. The performance parameters of wireless transceiver are shown in Table 1.

Table 1. Performance parameters of wireless communication transceiver

Parameter	Value result
Operating temperature	−35 °C–80 °C
Operating frequency	430 MHz
Transmitted power	10 dBm
Frequency modulation mode	FSK
Receiving sensitivity	−110 dB
Operating voltage	2.2–3.6 V
Operating frequency	1.2–1500 kbps
Communication distance	450 m
Emission current	60 Ma@10 dBm
Receiving current	10 mA

Based on the data in Table 1, set and adjust the signal receiving and transmitting device, and apply it to monitor the operating signals of electrical equipment. To obtain more reliable signal values, it is necessary to control the external interference suffered by the device. According to the power transmission model related to communication and interference links, the interference signal ratio of the target receiver can be obtained, and the transmission power (PTs) of the signal can be improved. GTs is the gain of the transmitting antenna, and GRs is the gain of the receiving antenna; Ls reduce the transmission path loss of signals, which can reduce the input interference to signal ratio of the receiver, maintain the system from unnecessary interference, and ultimately ensure the reliability of non information transmission.

Another anti-interference measure is to increase the anti-interference tolerance of the system. The receiver of the communication system can be represented as shown in Fig. 1.

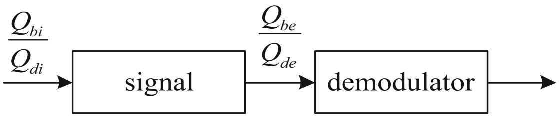


Fig. 1. Receiver signal ratio model

In Fig. 1, $\frac{Q_{bi}}{Q_{di}}$ represents the signal interference ratio at the input end of the receiver, $\frac{Q_{be}}{Q_{de}}$ represents the signal noise ratio at the input end of the information demodulator in the receiver, $M_Q = \frac{Q_{be}}{Q_{de}} - \frac{Q_{bi}}{Q_{di}}$ represents the signal interference ratio gain obtained from signal processing before the receiver has no demodulator, and T represents the loss of signal interference ratio after the completion of the gain processing. According to the content shown in Fig. 1, the above Settings are integrated, then:

$$R_j = (\frac{Q_{bi}}{Q_{di}})_{\max} = M_Q - \left[T + (\frac{Q_{bi}}{Q_{di}})_{\min}\right] \tag{1}$$

Therefore, by increasing M_Q and reducing T and $(\frac{Q_{bi}}{Q_{di}})_{\min}$, the interference tolerance of the system is increased, thereby improving the system's anti-interference ability against interference.

3 Electrical Equipment Condition Monitoring Method

The condition monitoring of the equipment is to evaluate the running condition of the equipment through various signal measurement, detection, processing and analysis methods, combined with the history and current situation of the system operation, and display, record and trend analysis of the equipment status, timely processing of abnormal conditions, and provide basic facts and data for the running condition analysis and equipment performance evaluation of the monitored equipment. According to the known structural characteristics, parameters and environmental conditions, and combined with the operation history of the equipment (including operation records and previous failure and maintenance records), the nature, degree, category and position of equipment failure are determined, the relationship between fault, symptom, cause and system is defined, and the development trend of fault is indicated [8, 9].

Therefore, based on the wireless communication framework, this study optimizes the current methods for monitoring the status of electrical equipment. The process of monitoring the status of electrical equipment is divided into three stages, corresponding to signal sorting, evaluation, and status diagnosis. The specific design concept is shown in Fig. 2.

3.1 Electrical Equipment Signal Acquisition and Sorting

Fourier transform frequency domain analysis is one of the most widely used signal analysis methods in the field of equipment operation status monitoring. The occurrence and development of faults usually cause changes in the frequency components of equipment

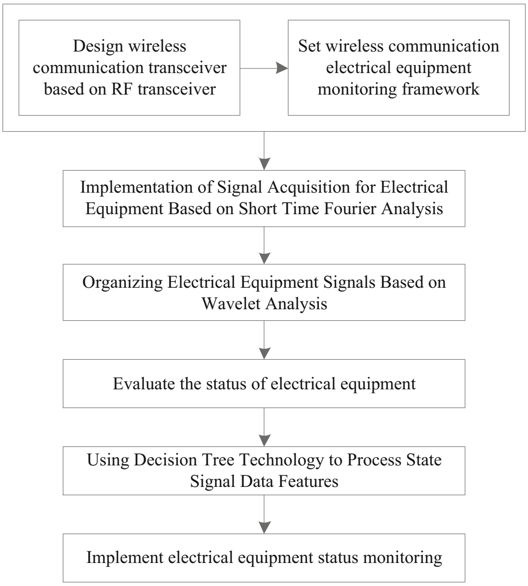


Fig. 2. Schematic diagram of electrical equipment status monitoring methods

vibration signals. The basis of frequency domain analysis is spectrum analysis, and the most commonly used method is Fourier transform, which decomposes complex signals into the sum of finite or infinite spectral components. The definition of Fourier transform is as follows:

If $f(t) \in Z^2(H)$ and $Z^2(H)$ represent square integrable real number spaces, that is, signal spaces with energy roots:

$$f(t)\frac{-\int_{-\infty}^{+\infty} F(\alpha)gd\alpha}{2\pi} \tag{2}$$

The traditional Fourier transform analysis method has made outstanding contributions to the development of signal processing technology. Fourier analysis is a global transformation, although it can connect the characteristics of the signal in the time domain and frequency domain, but only from the time domain and frequency domain observation, and can not combine the two organically. Therefore, this study optimized it and designed a short-term Fourier analysis process.

Short time Fourier analysis is a Time–frequency analysis method, also known as windowed Fourier analysis [10]. Its basic idea is to use the Fourier transform at the same time, before the basis function of the Fourier transform, multiply a time-limited function $k(t)g$ plays the role of frequency limit, $k(t)t$ plays the role of time limit, and then carry out time-domain localization analysis of signals through time-frequency double constraints. The short time Fourier transform is defined as:

$$K(\alpha, \delta) = \int_{-\infty}^{+\infty} k(t-\alpha)gd\alpha \tag{3}$$

After completing this operation, perform wavelet analysis on the signal. From the perspective of basis function, the characteristics of several corner basis (frequency analysis) in Fourier transform and time shifted window function in short-time Fourier transform are absorbed to form the basis function of oscillation and attenuation.

Wavelet analysis method is a time-frequency localization analysis method where the window size is fixed but its shape can be changed, and both the time and frequency windows can be changed. Wavelet transform observes signals at different scales (resolutions) and decomposes them into different frequency bands. It not only provides a comprehensive view of the signal, but also details of the signal. It has multi resolution ability, which means it has higher frequency resolution and lower time resolution in the low-frequency part, and higher time resolution and lower frequency resolution in the high-frequency part. The specific calculation process of wavelet analysis is set as follows:

$$\aleph_{c,\varepsilon}(t) = h^{-\frac{1}{2}} \varpi (\frac{t-u}{v}) \tag{4}$$

The wavelet transform of signal $x(t)$ is:

$$HT_x(c, l) = h^{-\frac{1}{2}} x(t) \varpi (\frac{t-u}{v}) dt \tag{5}$$

In the equation, c is referred to as the scale parameter, and l is referred to as the translation parameter. The scale parameter c changes the shape of the continuous wavelet, while the translation parameter l changes the displacement of the continuous wavelet. According to this section, organize the signals and store them in a suitable database for backup.

3.2 Assess the Status of Electrical Equipment

In this study, neural network technology is used to complete the real-time state assessment of electrical equipment. At present, the most commonly used neurons in typical examples of applied neural networks are perceptron and sigmoid unit. Generally speaking, the neural unit composed of linear activation function is usually called perceptron, and the neural unit composed of nonlinear continuous activation function such as S-shape function and bipolar S-shape function is called sigmoid unit. In this study, S-shape function and bipolar S-shape function are selected to complete the training and evaluation of the original signal.

A linear signal combination of a vector of real values is taken as the perceptron input, and some function is applied to calculate the input. If the output vector is larger than the threshold set in advance, the output is 1, otherwise the output is 1. Let a_1 to a_n be the input of a perceptron, then the output calculated by the perceptron is:

$$W(a_1, a_2, ..., a_n) = \begin{cases} 1, \mathit{if}\ e_0 + e_1 a_1 + e_2 a_2 + ... + e_n a_n > 0 \\ -1, \mathit{otherwise} \end{cases} \tag{6}$$

Among them, e_n is the weight value, which is a vector composed of a set of real number constants. It serves as a measure of the contribution of each input a_n to the output of the perceptron, commonly referred to as the contribution rate to the output. $-e_0$ is the pre-set threshold, which compares the output result with the size of the threshold. If the perceptron is to obtain a result with an output of 1, then the weighted sum of all input vectors $e_1a_1 + e_2a_2 + ... + e_na_n$ must be greater than the threshold $-e_0$. The decision plane equation of the perceptron is $\overrightarrow{e} * \overrightarrow{a} = 0$. Based on this perceptron, build sigmoid unit and set activation function. Based on the signal acquisition results, set the sigmoid unit structure as shown in Fig. 3.

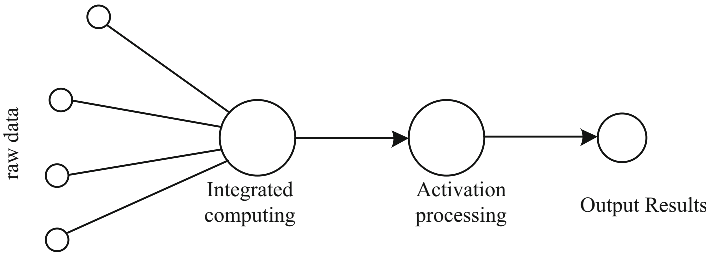


Fig. 3. Schematic diagram of sigmoid unit structure

Combined with the image, the signal training criterion is set. In this study, an error function is defined to determine the gap between the training output and the target output, so as to obtain the most appropriate weight vector. There are many ways to define the error function, and one of the most commonly used and convenient measurement criteria is:

$$U(\overrightarrow{e}) = \frac{\sum_{c \in C} (z_c - g_c)^2}{2} \tag{7}$$

Among them, C is the overall set of training samples, z_c is the target output, and g_c is the actual output. The goal of using delta rule is to minimize the above error function. The process of finding the minimum value using the gradient descent search method is to start with an arbitrarily set initial weight value, take small steps along the steepest direction of the surface, continuously modify the weight vector according to the direction of advance, and repeat the above process until the point in the entire space that meets the minimum error is found. Gradient descent algorithms are divided into two types: standard gradient descent and random gradient descent. The idea of the standard gradient descent algorithm is to summarize the errors of all samples before the weight update, that is, to sum multiple samples at each step of the weight update. Its gradient descent update rule is as follows:

$$\triangle\, e_i = \alpha \sum_{c \in C} (z_c - g_c) a_{ic} \tag{8}$$

The main idea of stochastic gradient descent is to update weights by looking at each training instance. This approach can sometimes avoid falling into local minimums because it uses different derivatives to guide the search. Using the above Settings, the collected signals are trained and evaluated as the preliminary results of condition monitoring.

3.3 Realize Real-Time Monitoring of Electrical Equipment Status

Apply data mining technology to cluster and mine signals in the trained signal database, in order to obtain the final electrical equipment status monitoring results. Using decision tree technology to complete this step based on the characteristics of signal data. Decision trees belong to recursive tree building algorithms, where each leaf point represents a data classification, and each tree point is associated with an attribute with information and gain. The value of this attribute can indicate the branching rules from each leaf point to its child nodes. According to this principle, the information entropy gain of the signal is calculated.

Hypothesis: A represents the total set of training samples, in which the number of training samples is represented by $|A|$; If the classification type has v' different values, then the training sample is divided into v' categories by classification category, each category is represented by V_i', and the number of training samples in each category is represented by $\left|V_i'\right|$, then the probability that any training sample belongs to $\left|V_i'\right|$ is $P' = \frac{|V_i'|}{|A|}$, and the average information entropy $\eta(A)$ of a given sample classification can be expressed as:

$$\eta(A) = -\sum_{i=1}^{v} P' \lg_2 P_i' \tag{9}$$

Set attribute V to contain n different values, divide the sample into n subsets, represented by A_n, and each subset has the same value in the sample. Set $|A_{ik}|$ as the number of samples after classification in the subset. The conditional entropy of this data classification can be expressed as:

$$\eta(\frac{A}{\sigma}) = \sum_{k=1}^{n} \left[P_k'(-\sum P_i' \lg_2 P_k')\right] \tag{10}$$

where, $P_k' = \frac{|A_k|}{|A|}$ and $P_{ik}' = \frac{|A_{ik}|}{|A_k|}$ represent the probability that the sample belongs to the target class. Generally, $\eta(\frac{A}{\sigma})$ and $\eta(A)$ are not equal. Attribute V provides information for classification, and the information entropy value of training sample classification changes. The change of information entropy caused by attribute V is called its information gain $Gain(V)$ for classification, then:

$$Gain(V) = \eta(A) - \eta(\frac{A}{\sigma}) \tag{11}$$

Use formula (11) to calculate the information entropy of the original signal data, and compare it with the historical data to determine the current operating state of electrical equipment. By organizing the content set in the previous text, the design of an electrical equipment status monitoring method based on wireless communication technology has been completed.

4 Experimental Demonstration and Analysis

In recent decades, the sudden failure of power plant equipment has caused great economic losses and casualties, so the fault diagnosis technology of power plant equipment is very necessary. Fault diagnosis is to analyze the real-time monitoring data of the unit and classify them, whether they belong to the fault state or normal state, and if they belong to the fault state, which kind of fault they belong to and so on. Thus, the problem of fault diagnosis is transformed into the problem of classifying monitoring data.

4.1 Equipment Data Samples

In the actual work of this research, a transformer fault sample was collected and sorted, which contains 10 sets of fault data, five typical faults: general overheating fault (fault 1), serious overheating fault (fault 2), partial discharge fault (fault 3), spark discharge fault (fault 4), arc discharge fault (fault 5). Since the actual measured gas content is a continuous value, in order to apply the decision tree method, we first need to discretization the data. For the convenience of calculation, it is divided into three levels based on its size: not high [0-5 ppm], high [0-5 ppm], and high ([0-5 ppm]). Based on the above settings, the device data sets used in this study were set.

Table 2. Equipment data sample

Signal group number	Total signal volume	Category of abnormal signals contained	Contains abnormal signal level
A1	10000	Fault 1	High
A2	10000	Fault 4, Fault 3	Higher
A3	10000	Fault 3	Not high
A4	10000	Fault 2	High
A5	10000	Fault 1, Fault 3, Fault 4	Not high
A6	10000	Fault 2	Higher
A7	10000	Fault 5, Fault 2	Not high
A8	10000	Fault 3, Fault 2, Fault 4	High
A9	10000	Fault 5, Fault 3, Fault 1	Not high
A10	10000	Fault 2	Not high

In this experiment, the data in Table 2 will be applied to analyze the application effects of the methods, basic methods (based on power hardware monitoring methods), and machine learning methods in this paper. In order to obtain more realistic experimental results, the experimental environment was set up in two parts: the laboratory and the factory. The specific experimental operation process and results are shown in the following text.

4.2 Abnormal State Recognition Rate Test Analysis

According to the preset experimental scheme, the following experimental results were obtained:

Table 3. Abnormal state recognition rate (unit: %)

Signal group number	Textual method		Basic method		Machine learning method	
Experimental environment	Laboratory	Factory	Laboratory	Factory	Laboratory	Factory
A1	90.39	90.53	90.77	80.7	90.83	85.12
A2	90.51	90.72	90.63	80.2	90.57	86.91
A3	90.3	90.26	90.8	81.19	90.94	86.58
A4	90.91	90.61	90.7	80.98	90.13	85.25
A5	90.01	90.15	90.79	81.34	90.48	85.29
A6	90.05	90.24	90.42	80.48	90.54	86.15
A7	90.73	90.17	90.58	80.84	90.42	85.64
A8	90.67	90.34	90.12	80.78	90.25	86.73
A9	90.66	90.67	90.44	80.81	90.2	85.73
A10	90.18	90.16	90.88	81.83	90.17	85.97

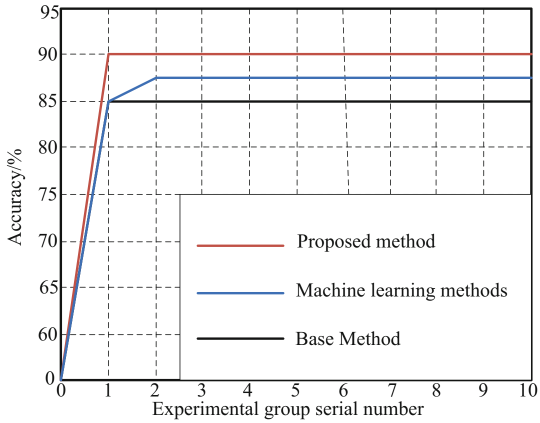
By analyzing the data in Table 3, it can be seen that the recognition abilities of the three methods are different in different experimental environments. Taking the laboratory environment as an example, in this environment, the abnormal state recognition ability of the three methods is roughly the same, and the whole is close, indicating that under the premise of no interference, the three methods have relatively close recognition results, and the overall recognition level is high. In the experimental environment of the factory, the recognition ability of the three methods changed greatly. The recognition rate of the proposed method does not fluctuate, while that of the other two methods decreases obviously. Based on the above experimental results, it can be determined that the proposed method has a strong ability of state recognition of electrical equipment.

4.3 Test and Analysis of Abnormal State Monitoring Accuracy

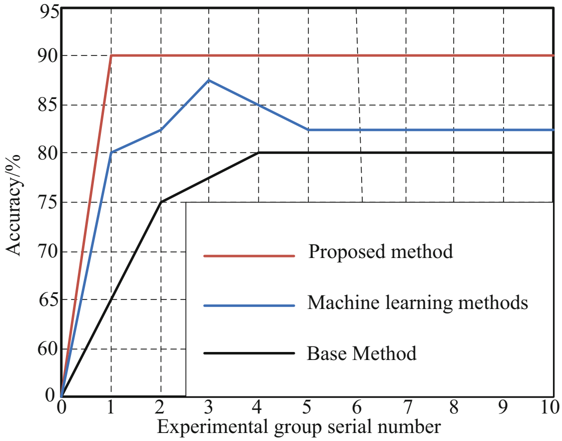
Based on the experimental results of the previous group, the accuracy of abnormal state monitoring for different methods is calculated using the following formula:

$$\partial = \frac{U_i'}{U_{all}'} * 100\% \tag{12}$$

where, U_{all}' represents all abnormal state data; U_i' indicates that abnormal status data is detected. According to this formula, the following experimental results are obtained.



(a) Laboratory environment



(b) Factory environment

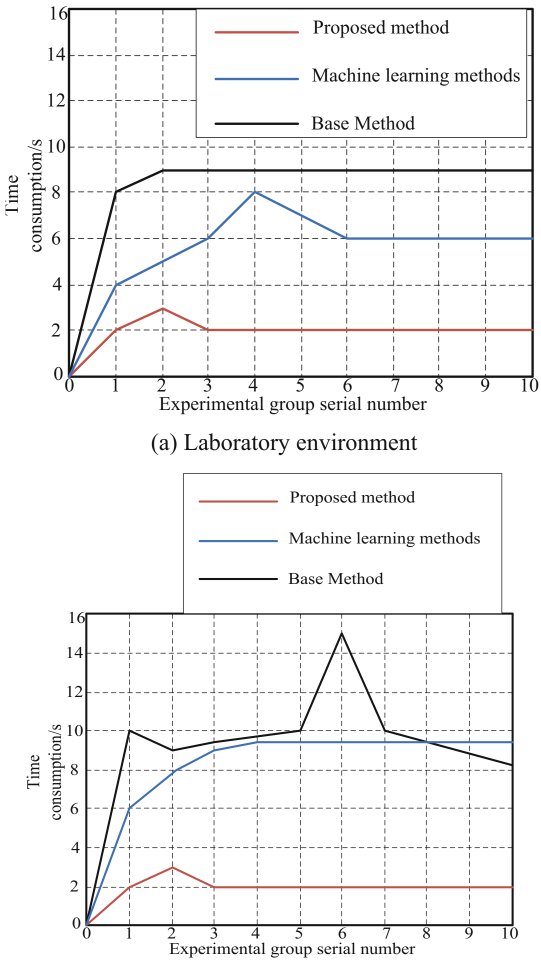
Fig. 4. Test results of abnormal state monitoring accuracy

By analyzing the experimental results in Fig. 4, it can be determined that in two different experimental environments, the method proposed in this paper has high accuracy in monitoring abnormal states of electrical equipment and will not change due to changes in the experimental environment. Compared with the methods in this article, the other two methods cannot obtain accurate monitoring results after application. In summary, the application effect of this method is better.

4.4 Time Consuming Test of Electrical Equipment Condition Monitoring

The test results of electrical equipment status monitoring time consumption are shown in Fig. 5.

Analyzing the experimental results in Fig. 5, it can be seen that under different experimental environments, the method proposed in this paper can obtain the operating



(a) Laboratory environment

(b) Factory environment

Fig. 5. Test results of electrical equipment status monitoring time consumption

data of electrical equipment in the shortest possible time, while the other two methods take relatively longer time. And when the experimental environment is a factory environment, the other two methods significantly increase the time consumption. From the above experimental results, it can be determined that the application effect of this method is better.

5 Conclusion

Aiming at the shortcomings of current electrical equipment condition monitoring methods in application, this study proposes a method of electrical equipment condition monitoring based on wireless communication technology, and verifies it through experimental demonstration. The experimental results show that this method has high application value, and it needs to be measured on a larger scale in the future research to ensure that this method has a wide range of application.

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