Eng Int Syst (2023) 6: 473–482

Engineering
Intelligent Systems

Power Equipment Fault Diagnosis and Prevention Based on Comprehensive Feature Quantity Evaluation

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Electric power technology has made a vital contribution to the development of today's society, and electrical equipment also occupies a very important position in railway operations. Since electrical equipment is very dangerous, with the improvement of living standards, people are paying increasing attention to the safety of such equipment. Frequent failure of power equipment can have serious consequences. Therefore, the important problem that needs to be addressed is how to effectively diagnose and prevent faults in railway power equipment. For this problem, the method of comprehensive feature quantity analysis can diagnose the fault of power equipment in time and effectively prevent the occurrence of the fault. Compared with the traditional fault diagnosis and prevention methods of railway power equipment, comprehensive feature quantity analysis mainly analyzed the causes of different types of faults and found out the corresponding internal components of the equipment for troubleshooting. The various types of causes were classified intelligently, and then these feature quantities were converted into data using computer algorithms to find similar variables. Lastly, the final preventive plan was obtained through model deduction. In this paper, an artificial neural network is used for data mining and analysis, and comprehensive feature quantities are examined to detect various indicators of the functioning of electrical equipment in a railway system, in order to diagnose and prevent power equipment faults. The effectiveness of the fault identification and the performance of the system were tested. It can be seen from the test results that when the load level was 80% and the number of training set samples was 68 and 65, the training set classification error rate and the test set classification error rate of the system would increase with the increase of the failure time. When the failure time was 0.1s and the load level was 80% and 100%, the response time of the system was not much different, but there was a difference of 0.82 in the mean square error value.

Keywords: comprehensive feature quantity analysis; power equipment; fault diagnosis and prevention of railway power equipment; feature mining; fault monitoring

1. INTRODUCTION

The safe and reliable functioning of the electrical equipment of a railway system helps to ensure that daily operations are not interrupted. There are many reasons for the failure of electrical equipment, and the factors responsible for failure are complicated. Traditional troubleshooting and diagnosis tend to rely on the staff's years of experience detecting faults and their causes, rather than on the analysis of scientific data. Therefore, the diagnosed cause of the fault is often inconsistent with the actual situation and eventually needs to be re-examined, which extends the maintenance cycle, causing major troubles for electricity companies and residents. When the railway power equipment fails, if the staff can find the cause of the equipment failure in time, and take corresponding remedial measures in time to prevent serious

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consequences of this failure, this can reduce not only the adverse economic and property damage caused by failure, but also serves to remind the staff to check and replace old components when necessary, or to improve and optimize the power technology. If these faults cannot be fixed in time, any damage to a particular piece of equipment will eventually have a negative impact on the operation of the entire power system. In severe cases, the equipment can explode and cause a fire. In addition to causing financial and property losses, these problems may endanger personal safety. Therefore, it is vital to create an intelligent system that can diagnose and prevent faults in the electrical equipment of railways . The method of comprehensive characteristic variable analysis can ensure the safety and reliability of the power equipment in the running state.

The method proposed for fault detection and prevention involves real-time monitoring of comprehensive characteristic variables of the operation status of railroad power equipment. The proposed system records the fault information when the power equipment fails, and analyzes the cause of the fault according to the information of the fault characteristics. This can help the maintenance crew to repair in time, reduce the time required for troubleshooting, and prevent equipment failure that could have serious consequences. The comprehensive feature quantity analysis identifies the fault, and a computer algorithm is used to calculate and determine the fault location according to certain statistical data. The main function of this system is to aggregate, process and classify the information displayed in different forms and at different time periods, and then formulate corresponding strategies according to the information in order to achieve the desired outcome. Because of its powerful performance, artificial intelligence technology is effective in systematic fault diagnosis. In particular, the data information analysis of the characteristics' parameters is carried out by means of the powerful self-learning ability and data processing function, and the obtained information data is recorded. By mining the characteristics' parameters, an appropriate algorithm model is established to improve the accuracy of fault identification.

The diagnosis and prevention of railway power equipment failures are very important since serious equipment failures may endanger life and property. Therefore, many scholars have studied this issue. Abdollah used the method of dynamic resistance measurement to study the faults such as the contact corrosion of gas circuit breakers in power equipment [1]. Arora analyzed several faults that were likely to occur in transformers and proposed that continuous monitoring and on-site diagnosis methods should be used to prevent the occurrence of these faults [2]. Shahid applied the Hilbert-Huang transform to the feature extraction of cable damage. The main purpose of this study was to predict the service life of the cable by identifying the degree of damage [3]. Abdin adopted a grid fault risk assessment method in a unified pricing market environment, mainly dealing with the energy cost consumption of different line faults [4]. Artigao examines and explains power generation technology and discusses the causes of generator-related failures in railway power equipment [5]. Qiao analyzed the fault diagnosis and prevention of wind turbines by examining the current state caused by the generator [6]. Although all the aforementioned studies focus on the failure of power equipment, most of the research methods are too complex, and costly in terms of money and time. Therefore, they cannot be applied to the current problems.

The use of comprehensive feature quantity analysis can simplify complex problems, and is a method suitable for resolving many technical issues. Therefore, it is also one of the most sought-after studies by international scholars. Xz used a convolutional network to extract and analyze the features of urban scene images, and classify the images according to the comprehensive features [7]. Yi performed a comprehensive phosphoproteomic analysis of a small population of cells using a comprehensive feature volume of isobaric markers [8]. Dackermann used the established frequency response function to construct a comprehensive feature quantity to identify the cepstral damage in the progressive damage structure [9]. Zhang constructed a comprehensive feature evaluation index in terms of quantity, instruction and ecology to evaluate the restoration potential of cultivated land, and used a clustering algorithm combined with the feature to analyze the restoration strategy [10]. Babatunde collected academic-related characteristics such as the average score and standard deviation of graduates to establish comprehensive feature evaluation indicators, and analyzed and evaluated the method of graduate employment in the construction industry based on the building information model incorporated into the teaching method of the Department of Education [11]. Although the above researches have mentioned the method of comprehensive feature quantity analysis, the research on fault diagnosis and prevention in terms of power equipment is relatively scarce. Therefore, the research direction of this paper is of great significance and can fill some gaps in this area.

The main purpose of this paper is to design is to design a system that enables timely fault diagnosis and issues an early warning that the functioning of electrical equipment is compromised. The two important modules of power equipment fault diagnosis and power equipment fault early warning were designed, and the power equipment fault detection index was established. The novel contribution of the paper is that it proposes a method of mining characteristic parameters using artificial neural network to establish a fault diagnosis and prevention system for power equipment.

2. DESIGN METHOD OF POWER EQUIPMENT FAULT DIAGNOSIS AND PREVENTION SYSTEM

2.1 Fault Diagnosis of Railway Power Equipment

(1) Railway power equipment

There are many types of power component modules in power equipment. These modules are roughly divided into two types: power generation plant and power supply plant [12]. In modern power systems, power equipment often has higher voltage levels. It is mainly responsible for the transmission and conversion of power in the power grid,

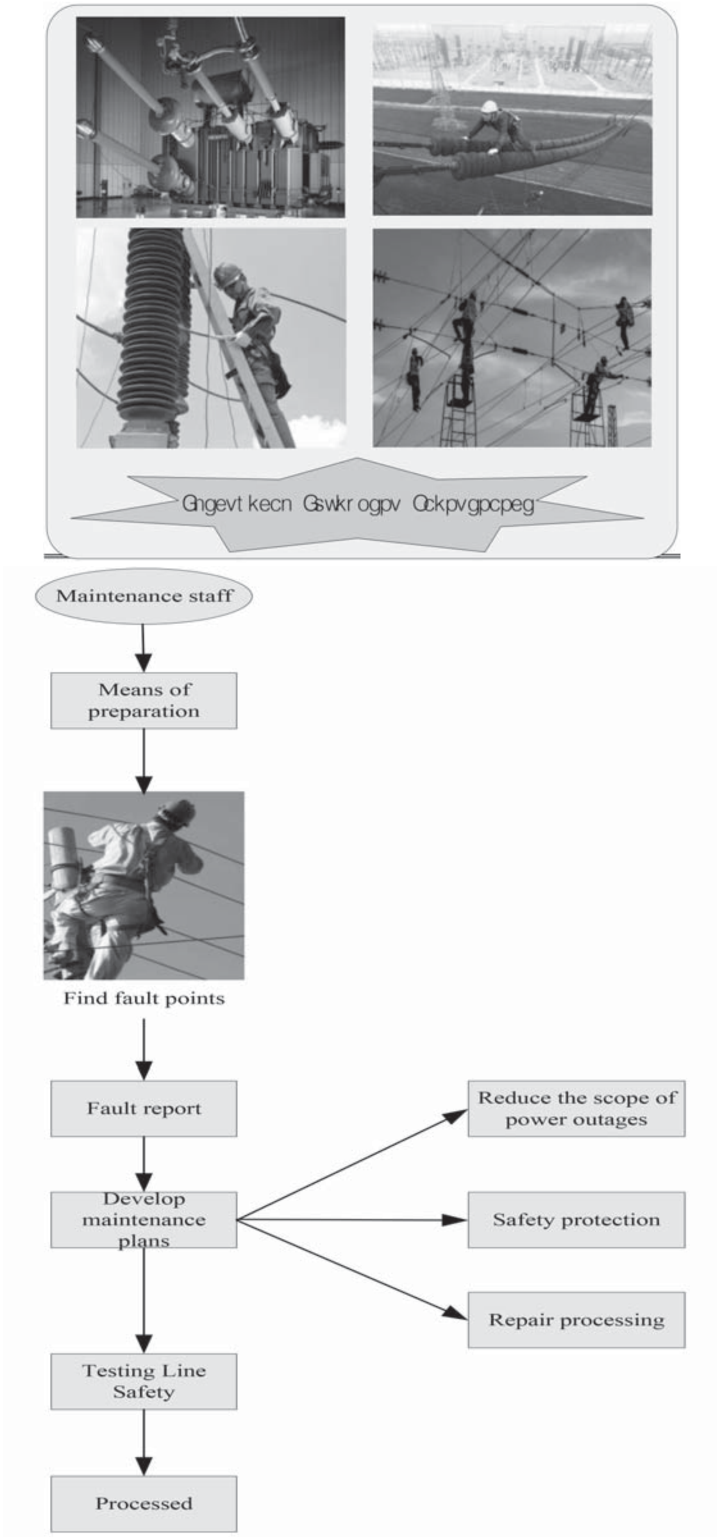

Figure 1 Maintenance of electrical equipment.

and is the key to supporting the operation of the entire power grid. Manual maintenance is often required in the daily maintenance of railway electrical equipment, and the maintenance of electrical equipment is often accompanied by high risks. The images in Figure 1 below show maintenance crews performing tasks on electrical equipment.

In the whole railway power system, the main function of electrical equipment is to perform voltage conversion and regulation [13]. The role played in the power transmission process is very critical, as it is related to the operation of the entire power system and the continuous stability of the power supply [14]. In addition, the manufacturing cost and manufacturing cycle of power equipment are very high, and most of the equipment is installed in the open air where, over time, it is eroded by the natural elements. Therefore, electrical equipment needs to be regularly maintained and/or repaired.

Table 1 Common electrical equipment failures.

Device	Cause of Issue
transformer	faulty tap changer, tank element
breaker	oil and gas sealing ring failure, insulation medium mutation
isolating switch	connector overheating, transmission failure
transformer	body overheating, high voltage breakdown, insulating medium leakage

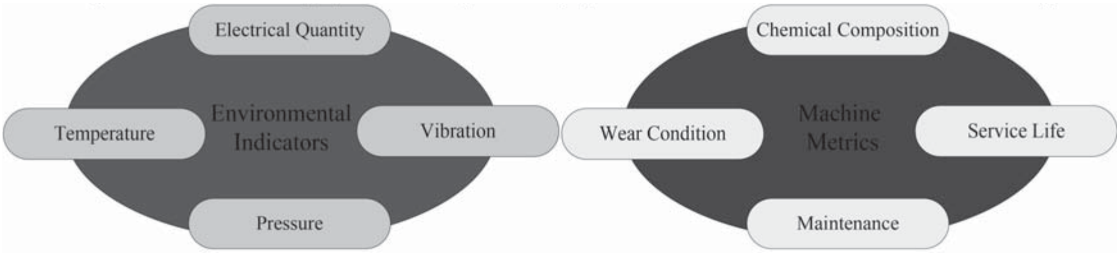

Figure 2 Schematic diagram of power index detection.

However, the traditional maintenance process includes many items and there are some problems that are not easily detected.

(2) Failure of electrical equipment

Comprehensive feature analysis is utilized for fault diagnosis and prediction of power equipment failure. This can update the condition and service life of electrical equipment in time. It also helps staff understand the operation of equipment and provides information about any maintenance work that is required, which greatly saves manufacturing costs and resources. When carrying out the comprehensive characteristic quantity analysis of power equipment, it is first necessary to have a comprehensive understanding of the type and probability of failure, as well as the severity of the potential accident. Then, according to the characteristics of the different electrical components and devices, corresponding effective measures are taken. For those key parts that are more prone to problems and have a large impact range but are difficult to find, major inspections are carried out. Some common fault problems are shown in Table 1.

(3) Power equipment testing indicators

In the case of the growth rate of the national economy, the number of railway power equipment is also increasing under the circumstance that the mileage of high-speed rail continues to increase, and the automation of power system is of great help to the railway power system. electrical equipment is easily affected by the use cycle of the components of the machine itself, as well as environmental changes in temperature and humidity [15]. The situation of each part of the affected equipment would change. When a change exceeds the planned range, this would affect the functioning of the electrical equipment. The power equipment detection indicators are shown in Figure 2.

2.2 Fault Diagnosis and Early Warning System Design

(1) Fault diagnosis module

There are usually two methods for diagnosing equipment faults. The *fault tree* displays the logical information of faults generated by the inference system, which is equivalent to inferring other related characteristic variables from the characteristic variables of a fault. Another method is the *expert system*, where a database inference model is built based on system failure knowledge [16]. It extracts the real-time monitoring data collected in the field and sends it to the fault knowledge database to carry out logical analysis, and determine the cause of the fault from the relationship of the characteristic quantities. These two methods are used according to the actual situation. The fault tree method is widely applicable, and its operation is more convenient. The expert system needs to establish a database inference model, so it is relatively expensive. Given this, smaller enterprises would not choose this method. Figure 3 shows the structure of the fault diagnosis module.

(2) Fault early-warning module

The fault early-warning module is used for the real-time monitoring of various index data of the electrical equipment in operation [17]. Then, the monitored data is returned to the set target value data center for calculation in time, and the obtained output vector is a comprehensive value. This comprehensive value is used to determine whether the vector value of a certain fault type meets the requirements. If the corresponding reference value is searched in the database, an alarm is issued, and corresponding emergency action can be taken through a pre-set program. After the staff receives the alarm, the corresponding solution measures are taken through the displayed fault-warning content. By means of comparison, the final result determines whether the content of the fault diagnosed by the system is correct. If there is no near fault type that can be used as a reference to compare the diagnostic results, the staff needs to further check the electrical equipment. The flowchart of the fault-warning module is shown in Figure 4.

(3) Design of railway power equipment fault diagnosis and early-warning system

The monitoring method of this system structure is based on the data obtained from sensors such as proximity switches and transmission interfaces installed on the electrical equipment site to monitor electrical equipment, and input it to the fault diagnosis module to generate a corresponding comprehensive characteristic parameter quantity of electrical equipment

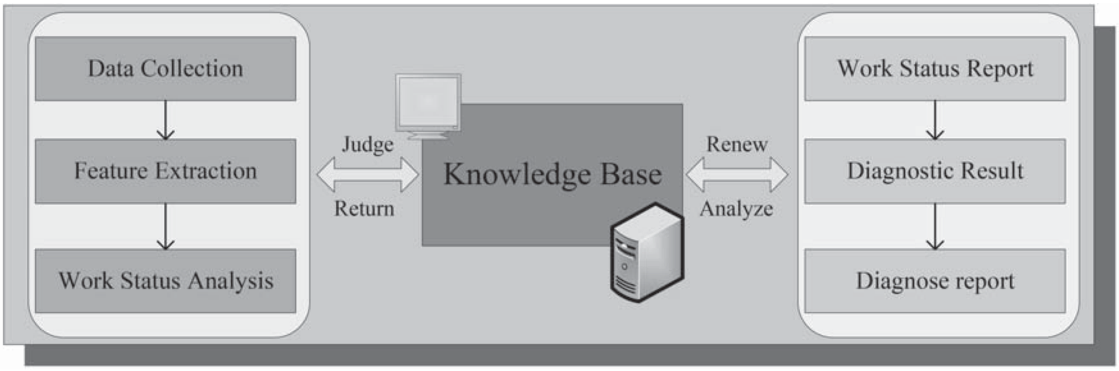

Figure 3 Structure of fault diagnosis module.

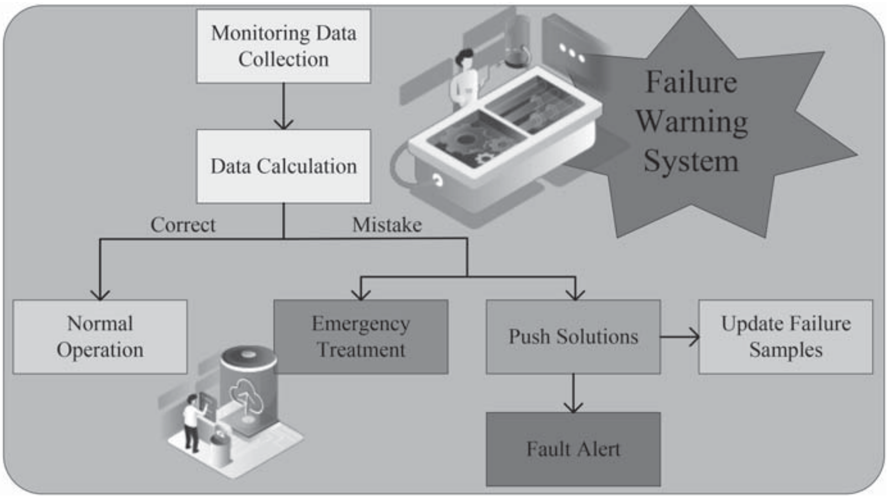

Figure 4 Flow chart of fault warning module.

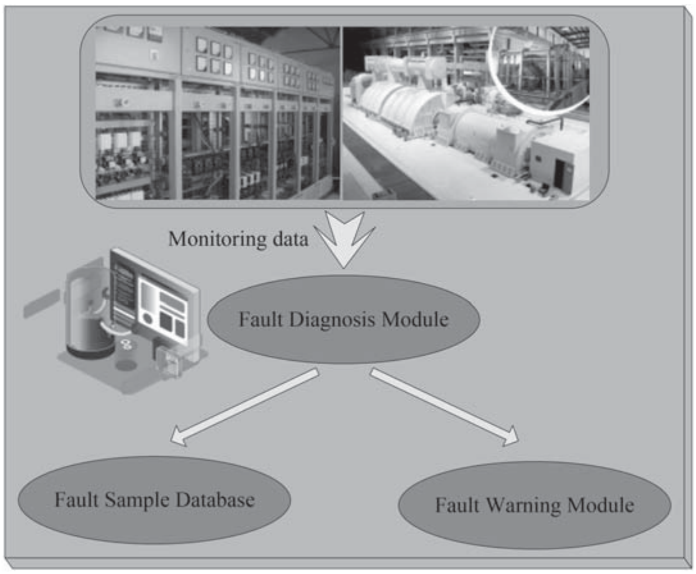

Figure 5 Flow chart of power equipment fault diagnosis and early warning system.

faults. Then, the detection data are sent to the calculation board for algorithm calculation. The electrical equipment fault diagnosis process is actually a comparison of the electrical equipment fault real-time state parameters with the parameter query system of the computer database, so as to obtain the real-time diagnostic data content and determine the cause of the fault. If it is found that if a parameter exceeds the expected value, it turns on the system warning through the fault-warning system, and responds according to the preset program, which will be displayed on the computer monitor. The diagram of the power equipment fault diagnosis and early warning system is shown in Figure 5.

2.3 Analysis of Characteristic Quantity of Railway Power Supply Fault

(1) Feature correlation data processing

The comprehensive feature quantity is the basis for fault detection, and the occurrence of faults changes the temperature [18]. When the electrical equipment is powered on and the equipment load is too high, this raises the temperature, and it is easy to detect the temperature change at this time.

According to the correlation of the amount of current, the feature extraction is carried out by means of horizontal and vertical comparison. The three-phase contacts that belong to the same electrical condition are regarded as a whole. For example, switch contacts such as capacitor cabinets and transformers include the three X, Y, and Z phases. At the same time, the temperature information of the three-phase contacts is monitored, and the difference between the three-phase contacts is obtained by the difference method as the characteristic detection data. T_X, T_Y, T_Z represents the temperature of the X, Y, Z three-phase switches in the same three-phase point library at the same time.

$$\left\{\begin{array}{c} T_{XY} = |T_X - T_Y| \\ T_{YZ} = |T_Y - T_Z| \\ T_{XZ} = |T_X - T_Z| \end{array}\right\} \tag{1}$$

Theoretically, if a current-carrying fault occurs, the temperature of the contact with the larger contact resistance is always higher than that of the other contacts. T_X and $T_{X\sim}$ represent the temperature of the upstream and downstream contacts of the A-phase, respectively. The differential temperature of the contacts of the same circuit is longitudinally compared:

$$\left\{\begin{array}{c} T_{XX\sim} = |T_X - T_{X\sim}| \\ T_{YY\sim} = |T_Y - T_{Y\sim}| \\ T_{ZZ\sim} = |T_Z - T_{Z\sim}| \end{array}\right\} \tag{2}$$

The value of similarity is a common indicator used to measure the degree of similarity between vectors [19]. It is the basis for then finding the nearest neighbor of the item to be predicted. Of the several commonly-used similarity measurement methods, cosine similarity has good performance. Therefore, cosine similarity is selected as the similarity measurement method. The cosine similarity calculation formula is:

$$sim(k_a, k_b) = \frac{k_a * k_b}{|k_a| * |k_b|} = \frac{\sum_{v \in S_{a,b}(r_{v,a} r_{v,b})}}{\sqrt{\sum_{v \in S_a}(r_{v,a})^2}\sqrt{\sum_{v \in S_b}(v_{v,b})^2}} \tag{3}$$

After calculating the similarity value, the M items with the highest similarity with the item to be predicted are selected as the nearest neighbors. According to the score data of the nearest neighbors, the predicted score value of the target project can be calculated. The score prediction formula of the project collaborative filtering algorithm is as follows:

$$P_{s_v,k_a} = \overline{r_a} + \frac{\sum_{k_b \in neighbors_{i_a}} sim(k_a, k_b) * (r_{v,b} - \overline{r_b})}{\sum_{k_b \in neighbors_{i_a}} sim(k_a, k_b)} \tag{4}$$

Relevance weighting is an empirical weighting method that affects the similarity calculation according to the number of times a user has rated or an item has been rated [20]. The calculation formula for the relevant weighted weight and the calculation formula for the weighted similarity are:

$$e_{k_a,k_b} = \begin{cases} Q/T & Q < T \\ 1 & Q \geq T \end{cases} \tag{5}$$

$$sim'(k_a, k_b) = e^*_{k_a,k_b} sim(k_a, k_b) \tag{6}$$

The correlation weight would affect the calculation of the similarity, so the change of the similarity value after weighting would also bring about a change to the nearest neighbor set of the item to be predicted. The scores of the items to be predicted obtained according to different nearest neighbor sets would also be different. Equation 7 is the score prediction formula after the correlation weighting has been introduced:

$$P'_{s_v,k_a} = \overline{r_a} + \frac{\sum_{k_b \in neighbors_{i_a}} sim'(k_a, k_b) * r_{v,b}}{\sum_{k_b \in neighbor_{i_a}} sim'(k_a, k_b)} \tag{7}$$

(2) Artificial neural network

An artificial neural network is a network formed by interconnecting a large number of neurons. Its structure is similar to the human brain neuron network, and a simple computing model is built on the basis of this structure. A neuron is the most basic unit of a neural network. Its receiver is responsible for receiving information, and its output is responsible for transmitting information. It is an adaptive nonlinear dynamic system consisting of a large number of simple basic element neurons connected to each other. A neural network adjusts the value of the transfer function by changing the weight relationship between neurons to control the threshold of the weight so as to meet the required accuracy requirements [21]. The neuron is the basic information processing unit of neural network operation. Figure 6 below depicts the neuron model.

$(y_1, y_2, \cdots, y_n)$ is set to be the input signal, $(q_{k1}, q_{k2}, \cdots, q_{kn})$ is the synaptic weight of neuron k, w_k is the output of the linear combiner of the input signal. The bias is d_k, and the activation function is $\varphi(\cdot)$. x_k is the neuron output, and the bias d_k is the external parameter of the artificial neuron k. It can either inhibit or strengthen w_k.

$$w_k = \sum_{i=1}^{n} q_{ki} y_i \tag{8}$$

$$x_k = \varphi(w_k - \theta_k) \tag{9}$$

After the input value passes through a certain neuron k, the output value is:

$$x_k = \varphi\left(\sum_{i=1}^{n} q_{ki} y_i w_k - \theta_k\right) \tag{10}$$

The activation function performs the transformation of the network input obtained by the corresponding neuron, also known as the activation function. It gives the neural network the characteristics of nonlinear mapping [22]. Commonly-used activation functions have the following three forms.

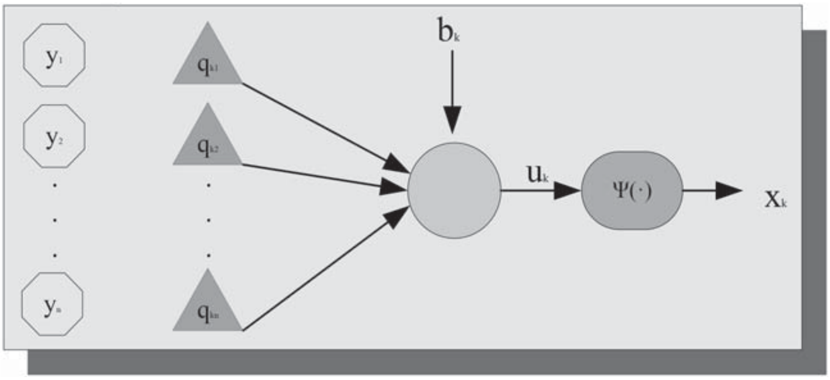

Figure 6 Nonlinear model of neurons.

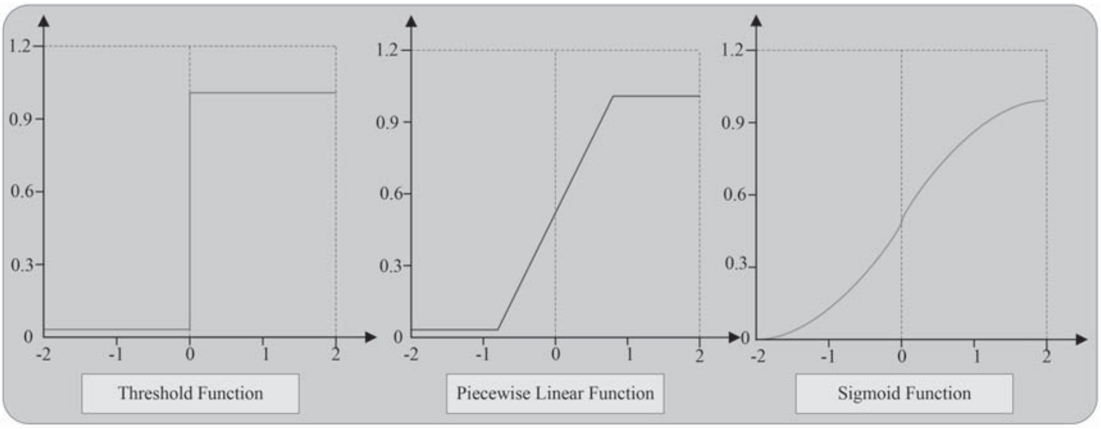

Figure 7 Activation function of a neural network.

The threshold function is:

$$\varphi(u_k) = \begin{cases} 1 & u_k \geq 0 \\ 0 & u_k < 0 \end{cases} \tag{11}$$

$$u_k = \sum_{i=1}^{n} q_{ki} y_i - \theta_k \tag{12}$$

The corresponding output is:

$$x_k = \begin{cases} 1 & u_k \geq 0 \\ 0 & u_k < 0 \end{cases} \tag{13}$$

A piecewise linear function is a linear combination that becomes a threshold unit as the amplification factor approaches infinity.

$$\varphi(u_k) = \begin{cases} 1 & u_k \geq 1 \\ \frac{1}{2} & -1 < u_k < 1 \\ 0 & u_k \leq 1 \end{cases} \tag{14}$$

Sigmoid function: the most commonly used function form is:

$$\varphi(u_k) = \frac{1}{1 + \exp(-cu_k)} \tag{15}$$

$$\varphi(u_k) = \tanh\left(\frac{u_k}{2}\right) = \frac{1 - \exp(-u_k)}{1 + \exp(-u_k)} \tag{16}$$

Threshold function, piecewise linear function, and sigmoid function are all monotonic and asymptotic [23]. The three function representations are shown in Figure 7.

For the fault identification and classification performance of neural network systems, the method of feature classification evaluation is usually adopted. There are four general feature classification performance evaluation methods:

m_R is set to be the number of misclassified samples in the training set, and M_R is the total number of samples in the training set. Training set classification error rate is:

$$\varepsilon_R = \frac{m_R}{M_R} \times 100\% \tag{17}$$

m_H is set to be the number of samples misclassified by the test set, and M_H is the total number of samples in the test set. Test set classification error rate is:

$$\varepsilon_H = \frac{m_H}{M_H} \times 100\% \tag{18}$$

m_R is set to be the total number of samples in the training set, A is the number of network neurons, $x^d_{(i,j)}$ is the ideal output value of the i output neuron of the j sample, and $x_{(i,j)}$ is the actual output value of the i output neuron of the j sample. Mean squared error for the training set is:

$$MSE_R = \frac{1}{AM_R} \sum_{j=1}^{M_R} \sum_{i=1}^{A} (x^d_{(i,j)} - x_{(i,j)})^2 \tag{19}$$

Table 2 Experimental sample dataset.

Load Level	Downtime	Training Sample Set	Test Sample Set
80% load	0.15s	68	340
	0.1s	65	325
100% load	0.15s	64	320
	0.1s	43	215
120% load	0.3s	41	205
	0.1s	28	140

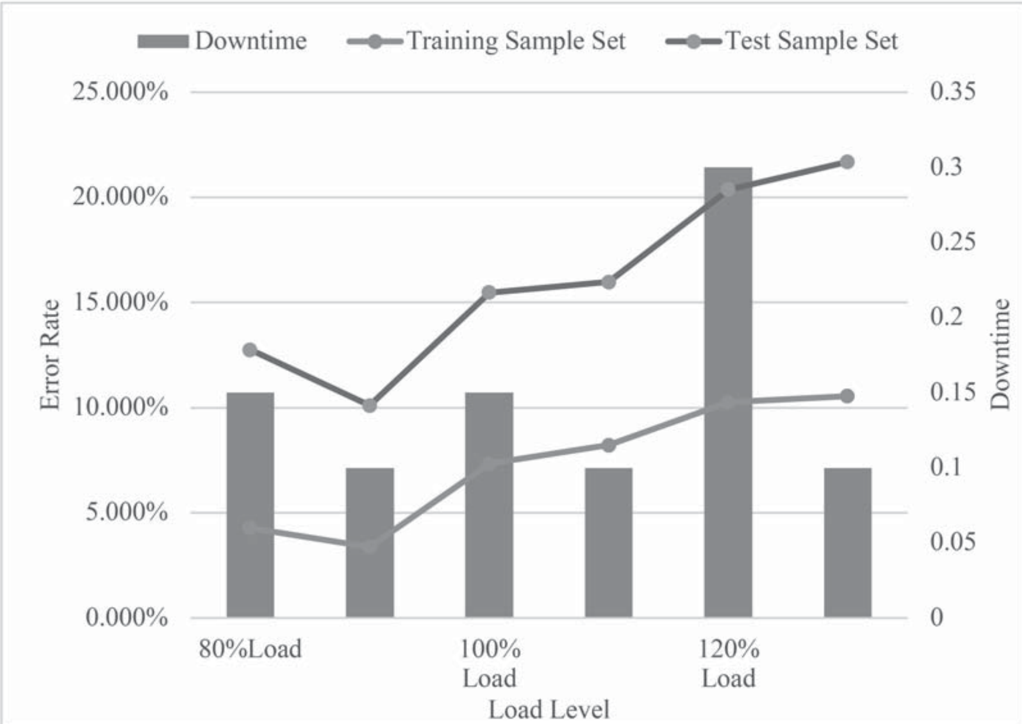

Figure 8 Classification of error rates for different load levels.

Mean squared error for the test set is:

$$MSE_H = \frac{1}{AM_H}\sum_{j=1}^{M_H}\sum_{i=1}^{A}(x_{(i,j)}^{d} - x_{(x,j)})^2 \qquad (20)$$

3. EXPERIMENT AND EVALUATION OF RAILWAY POWER EQUIPMENT FAULT DIAGNOSIS AND EARLY WARNING MODEL SYSTEM BASED ON ARTIFICIAL NEURAL NETWORK

The fault diagnosis and early warning system for railway power equipment is used to analyze the fault characteristics. Therefore, in order to explore the performance efficiency of the system, this experiment uses the sample dataset released by the Institute of Electrical and Electronics Engineers (IEEE) to test the system. The fault types are all set to a three-phase short circuit, and different fault times and load levels are set. The samples are divided into training samples and test samples. Twenty percent of the test samples are used for training, to ensure that the results obtained by the system test would not be affected by the proportion of training samples. These data are input into the power equipment fault diagnosis and early warning system to conduct systematic training and learning, and then experiments are conducted on test samples. The experimental sample dataset is shown in Table 2.

The sample datasets shown in Table 2 above is input into the system. The system performs the analysis through the comprehensive feature quantity. Then, the vector features are calculated, analyzed and learned through the artificial neural network, and the system can automatically generate a data analysis library about power equipment faults. After the training sample set is tested, the test data is input into the system. The selected comprehensive feature is calculated by threshold to obtain the optimal comprehensive feature. The system detects the test samples according to the comprehensive feature quantity, and uses the detected faults to predict and classify them according to the artificial neural network. Finally, the result is obtained. This experiment compares the classification error rate of the training set and the classification error rate of the final result of the test set, as shown in Figure 8.

The experimental data shown in Figure 8 shows that under different load levels and different fault occurrence times, the

Table 3 Experimental datasets with the same number of samples.

Load Level	Downtime	Test Sample Set
80% load	0.1s	160
100% load	0.1s	160
	0.15s	160
120% load	0.3s	160

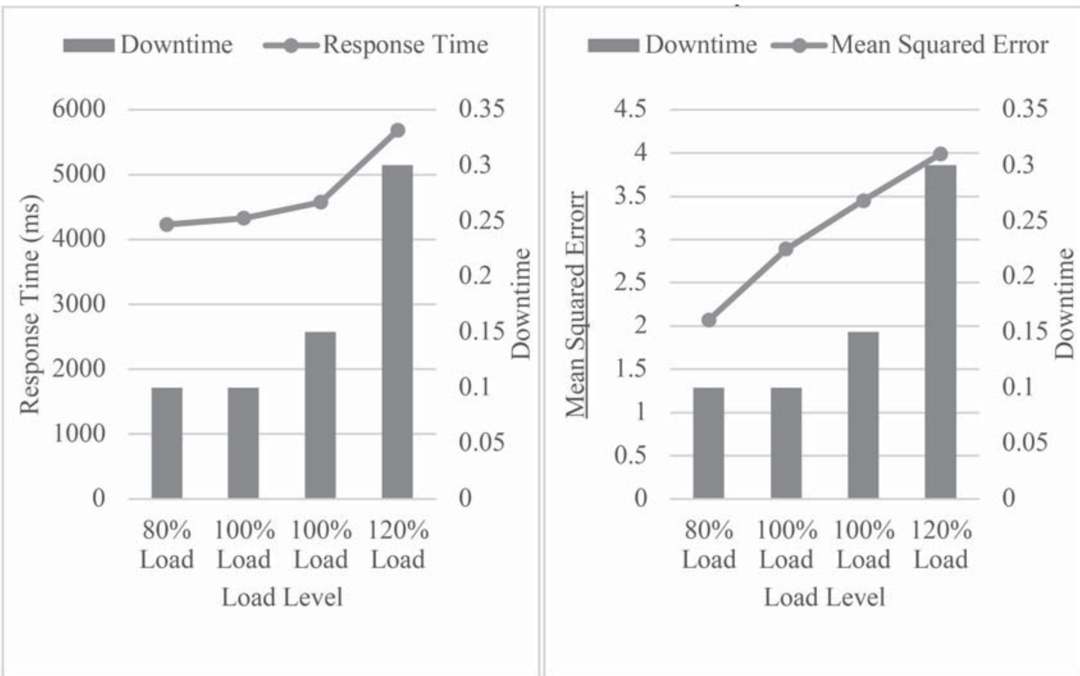

Figure 9 Response time and mean squared error at different load levels.

classification error rate caused by the classification of the training set and the test set by the system varies. By comparing the failure time and the number of samples under the same load level, the error rate of the system for failure classification would be affected. By comparing the experimental results when the load level is 80% and the number of training set samples is 68 and 65, it can be seen that when the number of samples is similar, the classification error rate of the training set and the classification error rate of the test set of the system would increase with the increase of the failure time. This is because the less number of times the electrical equipment fails, the higher the accuracy of the system's identification and classification of the fault. However, when the failure time of the equipment is the same, the more the number of samples, the lower the error rate of the system for fault identification and classification.

Through the above research, it was found that the load level, fault duration and the number of samples would reduce the accuracy of the system's identification of power equipment faults. In order to further explore the efficiency of the system, several sample data were extracted from the above sample dataset. The number of samples was set to the same number, and further experiments were carried out to determine the response time and mean square error of the detection system. The details of the experimental sample dataset are shown in Table 3.

The experimental sample data is input into the system, and the response time of the system and the mean square error of the final classification result are recorded. The statistics for the experimental results are shown in Figure 9.

It can be seen from Figure 9(a) that the system's response time to power equipment fault detection is affected by the fault duration and load level. However, when the failure time is 0.1s and the load level is 80% and 100%, the response time of the system is not much different. The response time of the impact system is affected mainly by the fault duration of the power equipment, and the two are positively correlated. It can be seen from Figure 9(b) that the mean square error value of the system for fault identification is affected by the load level and the fault duration. When the failure time is the same, the mean square error value increases with the increase of the load level. When the load level is the same, the mean square error value also increases with the failure time.

4. CONCLUSIONS

The main purpose of this study was to ascertain the importance of railway power equipment and the consequences of having electrical railway equipment that is faulty or prone to failure. The focus is on the design of fault-diagnosis and early-warning systems. The design of two important modules for the diagnosis of power equipment faults diagnosis and for early warning was explained in detail, and the causes of faults and the indicators that need to be detected were analyzed. It was proposed that an artificial neural network be used to mine characteristic parameters to establish an effective algorithm model to improve the accuracy of fault detection. Finally, experiments were conducted to test the efficiency and accuracy of the fault-diagnosis and early-warning systems based on an artificial neural network. For the experiments, different load levels were set for the power equipment at different fault times. The training set classification error rate and the test set classification error rate of the system's fault identification and classification results were compared, and the performance of the proposed system was evaluated according to the system's response time to fault occurrence and the mean square error value of the identification result. This research finally shows that the fault diagnosis and early warning system based on artificial neural network is far superior to other systems in terms of efficiency and performance, it has high accuracy in the perception and early warning of power equipment failure, and has strong practicability.

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