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Research Article

Design and Implementation of Fault Diagnosis System for Power Internet of Things Equipment Based on Neural Network

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The design and application of the equipment fault diagnosis system have been improved and upgraded, allowing it to effectively detect the equipment's operation status and promptly eliminate hidden faults, reducing the occurrence of unexpected accidents and improving the safety index of people's lives. The purpose of this essay is to design and apply neural network (NN) fault diagnosis system model in power Internet of things (IOT) equipment and explore its accuracy and effectiveness. The BP neural network (BPNN) algorithm was used to construct model of a fault monitoring testing of the power IOT equipment. Neural network is an algorithmic mathematical model that imitates the behavioral characteristics of animal neural network and performs distributed parallel information processing. The network parameters were as follows: there were four input layer nodes, seven hidden layer nodes, and five output layer nodes, the training times were 10000, and the allowable error was 0.002. In this paper, we use the IOT to detect model of a fault monitoring testing of power equipment designed in each sample, the success rate is as high as 97.5%, and the designed network structure and network parameters are reasonable. The trained loss is less than 0.001, and the nontraining set samples may be appropriately identified. It is clear that the NN has a high application for power equipment fault diagnosis in the IOT value.

1. Introduction

At present, due to the rapid development of smart grid, people pay more attention to the stability of power system operation. Smart grid is built on the basis of integrated, high-speed two-way communication network and through the application of advanced technology, to achieve the goals of reliability, safety, economy, high efficiency, environmental friendliness, and safe use of the power grid. Condition-based maintenance of power equipment is an indispensable key link. This kind of equipment is mainly used to monitor the operation status of power equipment in real time and then realize the maintenance of power equipment. With the rapid development of IOT technology, the fault diagnosis system of power equipment needs continuous improvement and optimization.

One of the outcomes of the continual advancement of information and communication technology is the use of IOT in power equipment. It will regulate the communication infrastructure resources and power system infrastructure resources in colleges and universities, enhance the power system information ability, and improve the utilization efficiency of the existing power system infrastructure equipment. In the specific application of condition monitoring and fault diagnosis technology of power equipment in China, even though there are many fault detection devices, such as multiple pulse intelligent cable fault tester, multimeter, etc., there are still limitations in practical application. The limitation is that it is difficult to solve the parameters of physical components: the form of system model structure and parameter changes caused by system failure is uncertain, or when the system has strong nonlinearity, there is still no effective algorithm. Some electric equipment is undergoing condition monitoring and problem diagnostics, it is still necessary to improve it, and there is a lack of in-depth exploration in some design and processing.

Yingyi proposed the topology structure of wind power equipment fault diagnosis system and introduced some key technologies involved in it, then analyzed the data, introduced the analysis and fault diagnosis method of the system, and finally analyzed the practical application of the system. Yingyi's research integrates the IOT and fuzzy clustering technology into the wind power equipment fault diagnosis system model, which improves the accuracy of fault diagnosis, but the effectiveness is low [1]. To identify the best lightweight convolutional NN (LCNN) for bearing defect diagnostics, Wang uses deep separable convolution, builds the LCNN structure, and provides a new decomposition level search space. Wang's research proposed a LCNN intelligent fault diagnosis method for bearings. The accuracy of this method is high, but the operation steps are complex [2]. In Leonardo's study, a control experiment was used to study the relationship between the capillary property of the IOT and the communication infrastructure provided by SG. This method is simple to operate but lacks stability [3]. Xing Tong combines rough set theory (RS) together and selects fuzzy system and NN algorithm to study the fault diagnosis of railway train ground wireless communication equipment. Based on rough set theory, Xing Tong simplifies fault sample data, removes redundant attributes, and reduces sample input. The research of Xing Tong adopts the method of theory and system fusion to analyze the fault diagnosis of railway train ground wireless communication equipment. The method is highly feasible, but the required accuracy is also high [4].

In this study, BPNN algorithm is used to build model of a fault monitoring testing of power IOT equipment. The network parameters and training times are set to 10000, and the allowable error is 0.002. Different learning rate and momentum factor are used to calculate the system error value to diagnose the fault of multiple IOT equipment. In this paper, we use the IOT to detect model of a fault monitoring testing of power equipment designed in each sample, the success rate is as high as 97.5%, and the designed network structure and network parameters are reasonable, and the trained loss is less than 0.001. It can be seen that NN can play a good role in power equipment fault diagnosis of IOT.

2. Principle about Power Equipment and NN

2.1. Power IOT Equipment. The history of research on Fault Diagnosis Technology in China is relatively short. The early stage is to understand the importance of equipment diagnosis technology at a relatively shallow level. Equipment fault diagnosis is developed along with the equipment management and equipment maintenance. Under the promotion of the European maintenance group alliance, the European countries are mainly guided by the comprehensive equipment engineering advocated by the United Kingdom: after the United States, as the guidance, they put forward the view of full production and maintenance. At present, there are many theoretical studies on equipment fault diagnosis technology, and many processing technologies have been tested, mainly for power equipment fault diagnosis. However, in the in-depth stage, this stage is based on the needs of modern management, and due to the rapid improvement of diagnosis technology, it takes pattern recognition, intelligent expert fault detection system, and calculation as the premise, improves the relevant experiments of equipment fault diagnosis in various aspects, and combines with the application in specific real life, gradually forming the distinctive fault diagnosis theory in China. We have developed a world-class fault diagnosis system for power IOT [5, 6].

For the status of power equipment fault diagnosis technology in the development of power industry, with the continuous expansion of China's power system scale, the probability of power equipment failure also increases, and the level of power equipment and security requirements are also improved; in particular after unattended substation is further popularized, people's requirements for power fault diagnosis system are also increased. Unattended substation is an advanced operation management mode of substation. It means that, with the help of computer telecontrol and other automation technologies, the on-duty personnel can obtain relevant information from a distance and control and manage the equipment operation of the substation. At present, China has a lot of substations that set up online diagnosis system, and some substations have reached the unattended condition. However, the types of electrical equipment in China's substation are diverse, and the structure is more complex. If there is a fault, it will increase the workload of the staff. Therefore, both the general substation and the unattended substation should set up online monitoring and fault diagnosis system as a way to enhance the diagnosis efficiency. However, in order to fully meet the unattended conditions, it is necessary to successfully construct the design of online monitoring and fault diagnosis in power equipment [7, 8].

2.2. NN and BPNN Algorithm

2.2.1. NN. NN provides a new theoretical approach and technical implementation for fault diagnosis of modern complex large-scale systems. NN is a parallel distributed information processing network composed of simulated neurons, which is similar to the characteristics of human brain. Because it has the ability of sorting out complex multistates, association, reasoning, and storage, it can make use of fault examples and diagnosis experience theory to practice and apply repeatedly. NN system is different from the high-level logic model of the previous fault diagnosis system. It is a low-level numerical model. Numerical models specifically refer to the use of mathematical logic and mathematical language, using numerical values to build scientific or engineering models. Its information processing is completed by the interaction of a large number of simple processing elements defined as nodes. The fault diagnosis experience is expressed by the connection weights covered in the network, so as to achieve a variety of nonlinear mapping relationship between fault and symptom. The real-time fault diagnosis system based on NN is an in-depth study on the fault diagnosis system of power equipment in the IOT. It provides a new method for

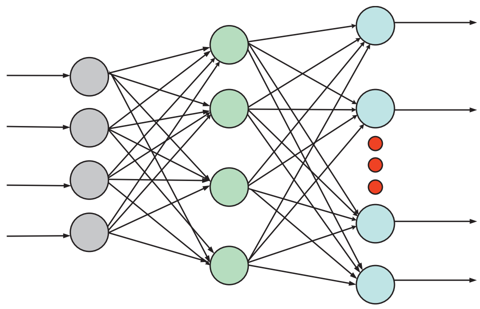

Figure 1: Fault diagnosis system network structure diagram.

the daily maintenance personnel of the fault diagnosis system, which will greatly improve the working efficiency of the system fault diagnosis [9, 10].

2.2.2. Overview of BPNN. BPNN is a type of error back-propagation algorithm that has many hidden layers [11]. Since there is an error between the output result of the neural network and the actual result, the error between the estimated value and the actual value is calculated, and the error is propagated back from the output layer to the hidden layer until it propagates to the input layer. BPNN typically contains an input layer, an output layer, and one or more hidden layers [12]. The BPNN is constructed as seen in Figure 1.

In Figure 1, the input layer has four neurons, the hidden layer has four neurons, and the output layer has eight neurons [13, 14].

According to Figure 1, the following is the outcome from every layer of neurons:

$$y = f\left(\sum_{i=1}^{n} w_i x_i - \theta\right), \tag{1}$$

where θ is the threshold and $f(x)$ denotes the activation function, which can be either linear or nonlinear. The activation function is the function that runs on the neurons of the artificial neural network and is responsible for mapping the input of the neuron to the output.

For the sigmoid function, which is utilized as the transfer function of the buried layer, type S function curve can just be used to describe the probability relationship between 0-1 and has an infinite approach; in fact, the sigmoid function does have a specific connection with the classification probability; it is a regularly used activation function:

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{2}$$

The global error function is defined as

$$E = \sum_{P=1}^{P} E_P = \frac{1}{2} \sum_{P=1}^{P} \sum_{j=1}^{m} \left(t_{Pj} - \gamma_{pj}\right)^2. \tag{3}$$

The output weight is adjusted to

$$\begin{aligned} \Delta w_{jk} &= \eta \sum_{P=1}^{P} \left(\frac{-\partial E_P}{\partial \mathrm{net}_{Pj}} \bullet \frac{\partial \mathrm{net}_{Pj}}{\partial w_{jk}} \right) \\ &= \eta \sum_{P=1}^{P} \left(t_{Pj} - \gamma_{Pj}\right) \bullet \gamma_{Pj} \left(1 - \gamma_{Pj}\right) Z_{PK}. \end{aligned} \tag{4}$$

Hidden layer weight adjustment is as follows:

$$\begin{aligned} \Delta v_{jk} &= \eta \sum_{P=1}^{P} \left(\frac{-\partial E_P}{\partial \mathrm{net}_{Pj}} \bullet \frac{\partial \mathrm{net}_{Pj}}{\partial w_{jk}} \right) \\ &= \eta \sum_{P=1}^{P} \left(\sum_{j=1}^{m} \partial_{Pj} \cdot w_{jk} \right) Z_{PK} \left(1 - Z_{PK}\right) X_{pi}. \end{aligned} \tag{5}$$

2.3. Condition Monitoring and Fault Diagnosis Technology

2.3.1. Condition Monitoring. Electrical equipment failure is caused by equipment aging accumulation in a certain stage; in particular the insulation objects of electrical equipment are mostly made of organic materials, which are prone to aging under the effect of external factors [15, 16]. The main component of power system is electrical equipment. Its failure will lead to power failure in a certain area or large area, which will definitely cause great property loss and bad social impact. Equipment condition monitoring is to measure part of the physical and chemical quantities by using multitype sensors and multimeasurement methods. These data can reflect the equipment's current state of operation. Monitoring is conducive to let the staff understand the operation status and operation process of the equipment, or some parts have inevitable problems. The "fault diagnosis" of equipment refers to the information and data processing results obtained by the system using the measured value according to the state detection, combined with the theory and experience of relevant devices to diagnose the severity, type, and position of the equipment fault and at the same time to provide opinions on the maintenance and treatment of the equipment. In brief, the analysis and judgment stage after characteristic quantity collection is fault diagnosis, condition monitoring, and feature acquisition steps [17].

2.3.2. Fault Diagnosis. Many different fault diagnosis methods are selected in many aspects, which is beneficial to deal with the equipment fault easily through various data of multisensor [18]. As far as possible to obtain a variety of information sources, the same information of various information sources in space and time is reorganized according to certain rules, so as to obtain the same interpretation or description of the equipment under test and then improve the evaluation of data reliability. The information of data is more perfect and accurate. Various types of fault diagnosis methods are used to properly integrate the information. It can also facilitate diagnosis and decision-making [19].

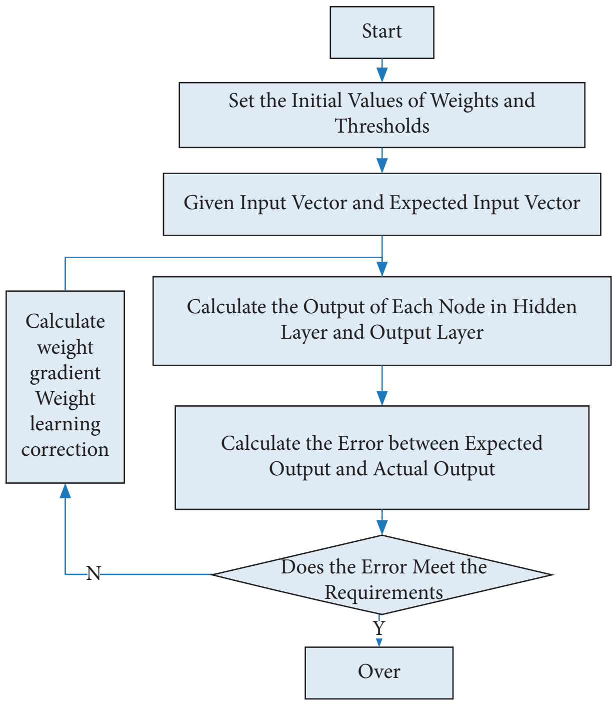

Figure 2: Flowchart of BP algorithm.

Using NN to strengthen the power equipment fault diagnosis has a series of advantages and good performance. In addition, it also has super neural computing power. Using NN to analyze the fault problem of power equipment, only a few simple nonlinear function combinations are needed, and complex physical model and manual control should not be constructed. It has the ability of self-operation and self-learning and can draw the height map and explain the nonlinear input-output relationship and judge the output after detecting the phenomenon again. Therefore, NN method has important value in power equipment fault diagnosis and focuses on the treatment of uncertainty [20, 21]. The flowchart of BP algorithm is shown in Figure 2.

2.3.3. Three Main Function Modules of the System

(1) Training Module. Before network training, network structure parameters should be provided to the system first. This stage can be realized by using the network parameters dialog box. There are relevant prompts for the network parameters and their data range required by the system. The staff and users are easy to operate, and the training times and training errors can be clearly seen at the same time of training [22].

(2) Fault Diagnosis Module. The fault diagnostic module is fused and analyzed after receiving the exact data information, and the sample parameters in the diagnosis database are compared to determine whether the IOT's power equipment is in good condition and its failure mechanism [23].

(3) Data Maintenance Module. Compared with the sample database and the historical database, the signal processing system is generally far away from the monitoring equipment in the transmission stage, and the data is easy to be affected and lost and is greatly disturbed by external environmental factors. At first, the data is converted from analog to digital, then compressed and packed after pre-processing, and then transmitted to the processing control center. With the help of communication lines, the data processing center can get the state data packet and then quickly unpack and sort out the data through a variety of mathematical methods. Using various analysis methods, the connection between two signals is used to find other signals in time domain. The application of digital information technology and intelligent technology has played an excellent role in the timeliness and accuracy of online monitoring and problem diagnostic system for power equipment data processing [24, 25].

3. Experiment and Analysis

3.1. Sample and Experiment Design

3.1.1. Training Sample Determination. The preliminary work of training data is the premise of network design and training. The scientific rationality of data selection and the accuracy of data transmission have a critical impact on network design. Let the network parameters be as follows: training times 10000, input layer node number 4, hidden layer node number 7, output layer node number 5, and allowable error 0.002, and take different learning rate and momentum factor to calculate the system error value. The processes for establishing the objective weight of state information between components using the value technique for each collection of data are as follows:

(1) The difference coefficient of state information j was calculated as g_i:

$$g_i = 1 - h_j\left(0 \le h_j \le 1\right). \tag{6}$$

(2) In each module, the degree of correlation between the tested matter-element and the standard fault matter-element was calculated:

$$K\left(N_i\right) = \sum_{j=1}^{3} w_j \cdot K\left(v_j\right), \tag{7}$$

where w_j is the weight coefficient, taking 1/3.

(3) Standardization:

The correlation degree is normalized using the following formula to make interpretation of the diagnosis findings easier; the purpose of normalization is to limit the pre-processed data to a certain range, thereby reducing the adverse effects caused by singular sample data:

$$K'\left(N_i\right) = \frac{2 \times K\left(N_i\right) - K_{\min} - K_{\max}}{K_{\max} - K_{\min}}. \tag{8}$$

Each group of data has been normalized, and some of the optimized sample data are shown in Table 1.

The transformation formula used in this paper is as follows:

Table 1: Fault diagnosis experience symptom samples of sensing nodes.

Fault type	Sample data									
	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
No fault K_1	0	1	0	0	0	1	1	0	0	0
Power supply grinding plate failure K_2	1	0	0	1	1	1	0	0	1	0
Storage module K_3	0	1	1	0	1	0	1	1	1	1
Communication module failure K_4	0	0	1	0	1	1	0	1	0	0
Control template K_5	1	1	0	0	0	1	1	1	1	0

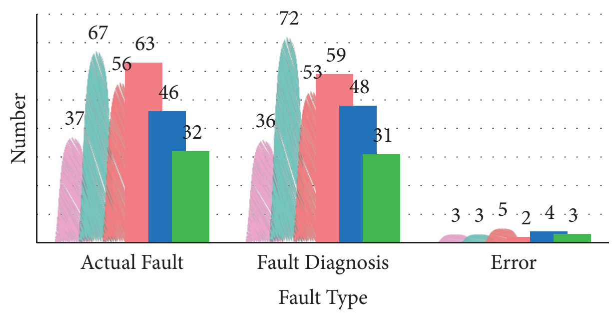

Figure 3: Accuracy judgment of node fault diagnosis test data.

$$\bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \cdot (HI - LO) + LO. \quad (9)$$

3.1.2. Design of Hidden Node Number. In this paper, we choose to set a small number of hidden nodes and then gradually increase the number of nodes to determine. The empirical formula used to determine the initial number of hidden nodes is as follows:

$$m = \sqrt{n + l} + \alpha. \quad (10)$$

3.1.3. Determination of Learning Rate, Momentum Factor, and Allowable Error. The allowable error is the condition for the training accuracy of NN, which is usually determined according to the complexity of the problem and the specific requirements. In this paper, we set it as 0.002, and the learning rate and momentum factor are selected according to the error. Let the network parameters as follows: input layer node number 4, hidden layer node number 7, output layer node number 5, training times 10000, and allowable error 0.002; take different learning rate and momentum factor to calculate the system error value.

3.2. Experimental Analysis

3.2.1. Accuracy Judgment of Node Fault Diagnosis Test Data. The BF NN algorithm is applied to the changes of each stage in the power equipment, and the fault symptoms of the sensing nodes are recorded, as shown in Figure 3.

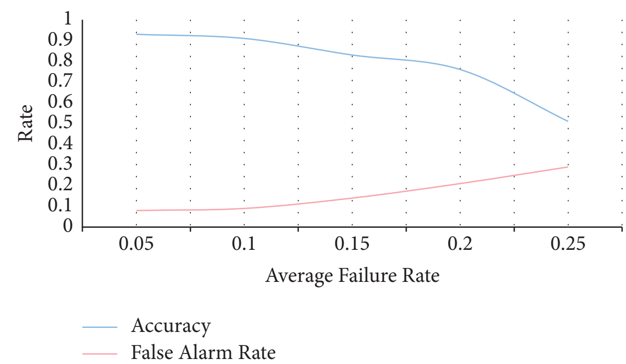

Figure 4: Comparison of fault accuracy and false alarm rate of BF algorithm.

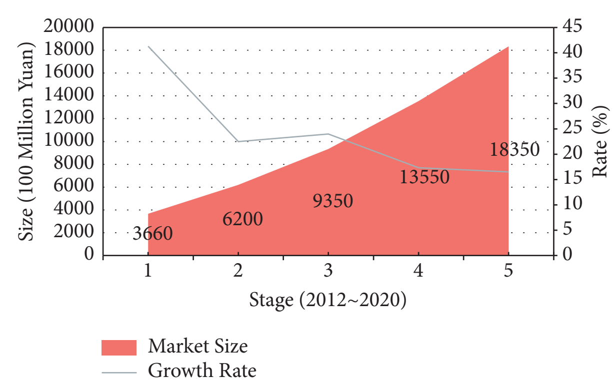

Figure 5: Market scale and growth rate of IOT.

As can be seen from Figure 3, the fault symptoms of sensing nodes in the algorithm have diversity and related characteristics. Combined with the advantages of different fault diagnosis methods, the system design should first clearly recognize that it must combine the advantages of different fault diagnosis methods to form a set of efficient and characteristic fault diagnosis measures for power equipment. Compared with the traditional fault diagnosis methods, the NN method has advantages in the case of the statistical characteristics of the background noise not being obvious, and the accuracy rate is relatively higher than the traditional method. However, as far as the NN fault diagnosis method is concerned, it also has many shortcomings. The common problem is that the system is relatively dependent on data. Although the contents of fault prediction, fault diagnosis, and condition monitoring are similar, there are differences in practical

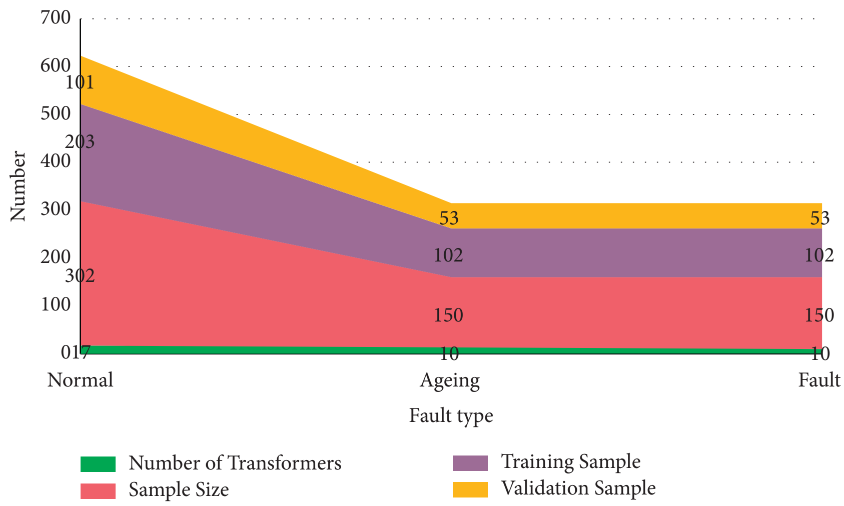

Figure 6: Training sample statistics.

application. Fault prediction is to predict all kinds of faults that may occur in equipment. Specifically, it is necessary to predict the time, location, and extent of failure. Fault diagnosis is aimed at all kinds of faults that have happened. It is to diagnose these faults. Firstly, find out the fault characteristics, then locate the fault correctly, analyze the fault degree, and finally diagnose. In order to effectively diagnose the fault of power equipment, it is necessary to analyze the electrical test data, routine inspection items, and operation and maintenance records of power equipment as data sources. Based on this, the normal power equipment operation has become the basis of power equipment condition detection. In view of the current situation of power equipment, diagnostic tests should be carried out as far as possible.

3.2.2. Accuracy Analysis of Fault Diagnosis. In order to explain the superiority of BF algorithm more precisely, the accuracy and false alarm rate of BF algorithm at each average node are compared, as shown in Figure 4.

It can be seen from Figure 4 that the fault diagnosis accuracy of the perception layer of the IOT increases with the increase of the fault rate in the network fault diagnosis with the change of fault rate. Specifically, fault diagnosis analysis is to analyze the physical process, chemical process, and causal process of electrical equipment fault. We summarize and sort out the characteristic quantity and dimension reduction of many equipment states and then use the identification technology such as fuzzy recognition and expert system to correctly judge the fault characteristic parameters and finally find out the cause, location, and nature of the fault. The equipment diagnosis information can be transmitted through LAN, and the fault of power equipment can be diagnosed by digital and network. If necessary, remote diagnosis can also be carried out in order to better complete the detection of equipment status and realize fault diagnosis. Remote transmission of information: In terms of technical equipment, we can also use a new type of equipment, namely, virtual diagnostic equipment. Some diagnostic systems have an alarm system on the client. The gadget can fully utilize the transmitting feature of network technology and upload data successfully. It can make the acquired signal achieve real-time effect.

Table 2: Error comparison of different learning rates and momentum factors.

Learning rate	Dynamic factor A	Minimum error value
0.5	0.4	0.0035
0.5	0.3	0.0141
0.6	0.2	0.0059
0.7	0.2	0.0028
0.7	0.3	0.0073
0.8	0.3	0.0321
0.8	0.2	0.0010

3.2.3. Analysis on the Application Market of Power Equipment of IOT. This paper analyzes the application value of IOT power equipment and investigates its market scale and growth rate in recent years in China, as shown in Figure 5.

Figure 5 demonstrates that, in recent years, the market scale of China's IOT power equipment has been expanding, and the development situation is on the rise, which indirectly reflects the value significance of building equipment fault diagnosis system. In practical work, there are still many deficiencies in the current state online monitoring, but it also shows some advantages and realizes the transformation from the traditional management mode to the state maintenance mode. Condition monitoring and fault diagnosis are different. The two are different. From the perspective of power system equipment operation, combined with the status quo of maintenance management, condition monitoring method is more common in practical application. Since the 1990s, SGCC has carried out the construction of power consumption information acquisition system. After years of promotion of marketing automation, the coverage

Table 3: Comparison of common IOT transmission protocols.

Agreement	Transport layer	Message mode	3G/4G/5G adaptability	LLN adaptability	Computing resource
MQTT	TPC	Publish/subscribe	Excellent	Commonly	10Ks RAM/flash
COAP	UDP	Request/response	Excellent	Excellent	10Ks RAM/flash
RESTful HTTP	TCP	Request/response	Excellent	Commonly	10Ks RAM/flash

rate of automatic collection of user power consumption information has increased year by year, and the application scope and effect have been gradually expanded, which has played an important role in marketing, production, and management. Through long-term practice, the power grid company has skillfully used technologies such as massive equipment access, multiprotocol support, and complex communication control in the acquisition system. It has initially met the technical conditions of domestic substation monitoring.

3.2.4. Sample Statistics. After many times of screening, the statistics of the sample database studied in this paper are shown in Figure 6.

Figure 6 shows that the samples in this work have been tested several times, with a detection success rate of 97.5 percent for the power transformer failure diagnosis system model built in each sample.

3.2.5. Error Analysis. In order to explore the NN model for power equipment fault diagnosis, different learning rate and momentum factor are used to calculate the system error value. The comparison results are shown in Table 2.

According to Table 2, the determined learning rate is 0.2 and the momentum factor is 0.8. In this paper, the NN, a high-level fault diagnosis tool, is used to effectively diagnose the internal fault of transformer. In the system test stage, all aspects scientifically and reasonably obtain the information of the power equipment of the IOT and seriously organize the sample training. From the determination of input and output vectors to the optimization of network structure parameters, a detailed comparative analysis is carried out, and the training system is tested many times. The results show that the BPNN has a good efficiency for power equipment fault diagnosis, and the corresponding fault diagnosis system has high accuracy and has good performance.

3.2.6. Design and Implementation of Diagnosis System. In order to analyze the feasibility of the diagnosis system designed in this study, the adaptability of various aspects of IOT transmission is the results of the comparison in Table 3.

It can be seen from Table 3 that the diagnosis system is short and accurate, easy to operate, and easy to maintain. Good IOT design allows operators to reset network parameters after updating the sample database to train the network until satisfactory results are obtained. According to the above network structure and training samples, the diagnosis results are consistent with the actual situation. It is necessary to extract useful information from complex signals. When the information provided by the equipment is more refined during operation, the equipment will show better diagnostic sensitivity. Not only may a fault characteristic quantity be caused by a certain fault state, but also usually many fault characteristic quantities reflect the same fault. Therefore, how to select fault characteristic quantity is one of the difficult problems we must solve. In the identification of fault state and normal state of power equipment, it is often misdiagnosed or missed diagnosis due to improper selection of characteristic quantity. There are overlapping parts of characteristic parameters between normal state and fault state in operating room, which may lead to wrong judgment, that is, fuzzy fault characteristic quantity. Therefore, this paper selects typical and effective fault characteristic parameters for condition monitoring to ensure the safe, economic operation of the power system.

4. Conclusion

This study focuses on the meaning and features of the NN and BPNN algorithms, examines condition monitoring and fault diagnostic technology, and covers the network training module, fault diagnosis module, and data maintenance module. It is clear that NN is useful in the deployment of a power IOT equipment diagnosis system. China is currently researching and implementing a condition-based maintenance system. The development of fault diagnostic and prediction technology for power equipment can detect the present state of operation of the equipment in real time, locate the equipment's latent defect in real time, and prevent unanticipated accidents. Through the combination of NN and IOT equipment, the state information of power grid or the operation status of various equipment can be detected intelligently. When an emergency occurs, the IOT can timely transmit accurate data information to the command center, which is conducive to the emergency personnel to prepare the required equipment in advance and immediately start on-site maintenance or replacement of parts, so as to improve the efficiency and ability of handling accidents.

The research results show that, in this paper, the BPNN algorithm is used to build model of a fault monitoring testing of power IOT equipment. The network parameters and training times are set to 10000. Each group of data is normalized, and the system error value is calculated with different learning rate and momentum factor. The fault diagnosis of multiple IOT equipment is carried out. The detection success rate is as high as 97.5%, and the designed network structure is also designed. And the network parameters are reasonable, the trained loss is less than 0.001, and the nontraining set samples may be appropriately identified.

Data Availability

This article does not cover data research. No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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