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Research on Fault Diagnosis of Rotating Equipment Based on Artificial Intelligence

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Abstract: *Rotating equipment is widely used in large industrial and mining enterprises, so its safe and stable operation is of great significance. With rapid development of artificial intelligence algorithms in recent years, many researchers apply them to the fault diagnosis of rotating machinery and equipment. This paper takes a company's rotating equipment as an object, discusses artificial intelligence algorithms suitable for remote fault diagnosis. Then, taking circulating water pump as an example, it summarizes the characteristic vectors, monitoring methods and fault types of circulating water pump. Based on operating status and characteristic parameters of the equipment management system accessed to circulating water pump, it designs four types of typical artificial intelligence algorithm models, and assesses its accuracy and effects through simulation software. In this way, it supports rapid diagnosis and analysis of the existing faults, points out the cause of the fault in time, effectively reduces the number of unit shutdowns for maintenance, extends the cycle of unit operation, and provides reliable guarantees for the safe operation of energy equipment.*

Keywords: *Artificial intelligence, Rotating machinery, State monitoring, Fault diagnosis*

1. Introduction

Most industrial and mining enterprises still adopt regular maintenance of the auxiliary equipment system, which not only consumes a lot of financial and manpower, but also fails to find the fault in time, which brings economic loss and excessive manpower waste. Therefore, it is of great significance to monitor the auxiliary equipment and system condition, and provide diagnosis of possible faults. At the same time, with the in-depth implementation of the dual-carbon policy and energy saving and emission reduction work, how to reduce electricity cost and improve efficiency has become the focus of enterprise in production and operation [1].

Auxiliary machinery mainly includes rotating machinery such as pump and fan (such as circulating water pump, fan, compressor, etc.). These rotating machinery have many common fault modes: fault of the mechanical body (rotor unbalance, rotor misalignment), bearing fault (such as bearing damage), lubrication system fault (such as oil pump fault, pressure regulating valve fault), drive motor fault (motor bearing damage), etc. Broadly speaking, equipment fault diagnosis consists of main links such as state monitoring, fault diagnosis, condition prediction, safety assurance, and maintenance decision-making. Equipment state monitoring and fault diagnosis are an organic whole: state monitoring is the basis, prerequisites and necessary means of fault diagnosis; while fault diagnosis is a factor in decision-making by comprehensively using monitoring data and information [2]. The purpose of this research is to optimize the equipment maintenance cycle, extend the equipment service life, reduce the equipment maintenance cost, reasonably and correctly evaluate the equipment status, and through "deterioration warning, technical diagnosis and trend analysis, equipment improvement, reliability improvement, physical examination analysis, physical examination report", establish a complete set of solutions for "remote fault diagnosis of auxiliary machinery".

2. Function Design for Auxiliary Machinery State Monitoring

State monitoring part accesses relevant monitoring data through the equipment management system, monitors the equipment in real time according to certain monitoring methods, accesses the current status information of the equipment, understands and grasps the dynamic operating status of the equipment to support real-time data display, historical trends and abnormality warning. If the equipment is abnormal, the monitoring system will give a warning message for the relevant personnel to take action (shutdown or fault diagnosis, etc.). Taking the circulating water pump as an example, we will study how to determine, monitor and analyze its operating state monitoring parameters.

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2.1. Determination of State Monitoring Parameters

Equipment fault is often manifested in certain states, and these states are contained in specific signals. We monitor and diagnose equipment mainly by accessing these signals and then analyzing them to determine equipment faults. Many signals can characterize equipment faults, such as vibration, temperature, pressure, and electrical signals. Depending on the fault characteristics, various signals have varying sensitivity to equipment faults [3]. Circulating water pump belongs to high-speed rotating machinery. Vibration is an inevitable phenomenon during its operation. Vibration contains a large amount of information during the operation of the circulating water pump. When it fails, the fault information is certainly included in the vibration signal. Therefore, analysis of vibration signals can help us identify equipment faults [4].

Circulating water pump is a device driven by the electric motor. It is also very important to monitor electrical parameters such as current and voltage, because these parameters directly characterize the operating status of the motor and the circulating water pump body, which are very useful for device fault diagnosis [5]. For example, when friction occurs between the rotating parts and stationary parts of a circulating water pump, not only vibration and temperature change, but also current changes.

Therefore, state monitoring parameters of the fan are mainly based on vibration and temperature, while parameters such as current and pressure are also considered. Based on the above analysis, by combining the actual situation of the on-site measurement points, we monitor the condition of the circulating water pump, the motor working condition, the working condition of the lubricating oil system and the bearing according to the analysis results of different parameters.

2.2. State Monitoring and Analysis

The online state monitoring of circulating water pump is mainly to complete the monitoring and simple analysis of the status information of rotating machinery equipment. The online monitoring system comprehensively uses the accessed data to judge and identify the operating status of the circulating water pump. It is required that the monitoring system can quickly determine the operating status of the circulating water pump, and can accurately tell whether the circulating water pump unit is in a normal state or an abnormal state. This system combines the most value analysis method and the trend analysis method to monitor and analyze the state of the circulating water pump, identify whether the equipment is operating normally.

2.2.1. The Most Value Analysis Method

The most value analysis method is to set a threshold value for the monitoring data. The measuring point value within the allowable range of the threshold value is regarded as normal, while the measuring point value outside the range is regarded as a warning condition. At this time, it is necessary to balance the system or stop the system operation, so that the measuring point value returns to the normal level range. Usually, a threshold is set for the numerical measuring point value to set the allowable range of the system, and the threshold size is usually calculated based on experience, field operation records, or statistics of actual measured values. In the equipment state monitoring technology, the most value analysis method is a commonly used online monitoring method; in the fault identification method, threshold value analysis is the fastest monitoring method, which only need comparatively judge the data value and the threshold value of the monitoring point to master the equipment status [5], as is shown in Figure 1.

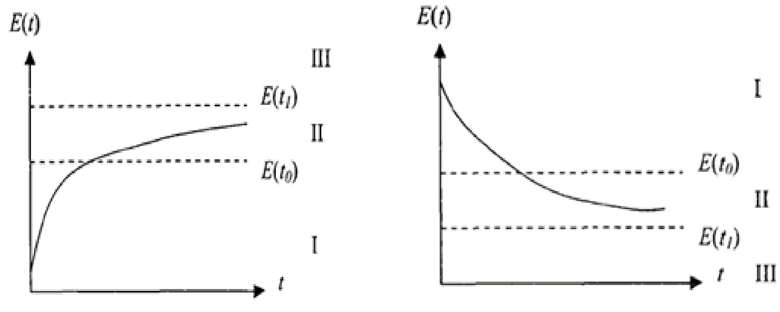

Figure 1: The most value analysis method

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2.2.2. Tendency Analysis Method

Tendency analysis method, also called trend analysis method, is a monitoring method for discriminating and analyzing the slope of the observation curve (that is, the value change rate) formed by the measuring point value of the monitoring point on the time axis. If the slope of the observed value curve is not within the specified range, rotating machinery equipment fault diagnosis system of the circulating water pump should notify the on-site personnel of the equipment abnormality, so that measures can be taken to return the trend (slope) to a normal level or stop processing. The trend analysis method is a monitoring method with predictive properties. Its essence is to predict the change trend of the future measuring point curve through the size of the curve slope. If the current slope of the measuring point curve is too large, the measuring point value of the system may exceed the normal value at some point in the future. The trend analysis method can be used to predict the behavior of the observation curve. Before unstable factor appears in the rotating machinery system, it can be adjusted to reduce the alarm situation that the measuring point value exceeds the standard value [6].

2.2.3. Artificial Intelligence Method

With the continuous improvement of artificial intelligence algorithms and deep learning theories, artificial intelligence models have been continuously applied to equipment fault diagnosis, prediction and early warning services. The general steps are as follows:

(1) Study the structural principles and operating characteristics of the system equipment (circulating water pump) to be diagnosed, propose and summarize the types of faults and their symptoms;

(2) Accumulate a large amount of empirical and intuitive knowledge through derivation of modeling theory, communication with experts and on-site operators, and summarize samples with typical significance;

(3) Determine the structure of the artificial intelligence algorithm according to (1), which specifically includes the following two sub-steps:

(a) Blur each input, determine the number of neurons in the quantization input layer and the number of neurons in the output layer;

(b) Determine the number of neurons in the hidden layer of the fuzzy network and the overall structure of the algorithm network.

(4) According to (2), train the BP network part of the fuzzy BP network;

(5) Provide diagnosis based on the knowledge in the knowledge base and the fuzzification and anti-fuzzification functions.

Fuzzy logic reasoning is based on the theoretical basis of fuzzy mathematics. Through the method of membership function, by combining the professional theoretical knowledge in operation of circulating water pump equipment, the fault symptom knowledge base is established. The most important link in fuzzy logic reasoning is the determination of the membership function. The membership function is a self-defined function that determines the main fault according to the degree of influence of the factors influencing circulating water pump equipment operation (i.e., symptom parameter) on the circulating water pump. There are many ways to establish the membership function, mainly based on the operating regulations for different parameters, actual experience and field experience. This paper divides the main fault domain of the circulating water pump into 13 typical faults $u_i (i = 1, 2, \cdots, 13)$, and the symptom domain is divided into 17 typical symptom parameters $x_j (j = 1, 2, \cdots, 17)$. In the symptom parameter, 0.0 is taken as the parameter falling to the lower limit fault alarm value, and 1.0 is taken as the parameter rising to the upper limit fault alarm value. For two-way fluctuations, all parameters must be referred to, and 0.5 is taken as the normal operating value. If there is only need to refer to positive fluctuations, that is, only parameters of the upper limit fault alarm value needs to be considered, take 0.25 as the normal operating value. If there is only need to refer to negative fluctuations, that is, only parameters of the lower limit fault alarm value need to be considered, take 0.75 as the normal operating value [7].

For example: For a parameter x, its normal value is x_0. If we only need consider its lower limit alarm value, that is, if the value is greater than x_0, it will not cause system fault, and if the value is less than x_0, it means that a certain aspect of the system has begun to deteriorate, or it breaks down. Hence,

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we regard the condition with a parameter value greater than x_0 as normal and take a value of 0.75. From this, the membership function of this parameter can be established as follows:

$$u(x)=\begin{cases}0.75 & x>x_0\\ 0.75\times\dfrac{x-x_{\min}}{x_0-x_{\min}} & x\le x_0\end{cases} \tag{1}$$

In the formula, $x_{\min}$ is the lower limit alarm value of the parameter.

Determine the membership function of each symptom according to the above method, and build a training sample set based on this. See Table 1 for details.

Symptom set in Table 1: A. big X-direction bearing vibration of circulating water pump; B. big Y-direction bearing vibration of circulating water pump; C. high temperature in drive end bearing of circulating water pump; D. high temperature in free end bearing of circulating water pump; E. high temperature in motor bearing; F. high temperature in motor coil; G. Large motor current; H. Large motor bearing vibration; I. Low pressure of circulating water pump lubricant.

Set of equipment faults: F1. Dynamic and static friction; F2. High lubricating oil temperature; F3. Unbalanced rotor; F4. Small amount of lubricating oil; F5. Circulating water pump bearing damage; F6. Motor bearing damage; F7. Filter blockage; F8. Air preheater blockage; F9. Incorrect coupling gap; F10. Foreign body in the fan; F11. Anchor bolt looseness; F12. Air duct leakage; F13. Oil pump fault; F14. Pressure regulating valve fault; F15. Unbalanced rotor; F16. Oil system leakage; F17. Impeller damage; F18. Small bearing clearance of circulating water pump.

Table 1: Knowledge table of fault symptoms

FAULT	No.	Symptom								
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
F1	**1**	0.9703	0.9685	0.6946	0.8418	0.6946	0.0632	0.8134	0.5192	0.8286
	2	0.9045	0.9164	0.8503	0.6865	0.6568	0.0806	0.7853	0.5072	0.8968
F2	**3**	0.1951	0.1126	0.8156	0.8076	0.9516	0.0000	0.0000	0.0291	0.5757
	4	0.1589	0.2017	0.9576	0.9456	0.8259	0.0000	0.0000	0.1003	0.3492
F3	**5**	0.9665	0.7503	0.6238	0.6531	0.1069	0.0000	0.0000	0.9556	0.4049
	6	0.9329	0.8571	0.2953	0.0868	0.6869	0.0000	0.0000	0.9035	0.5078
F4	**7**	0.4575	0.4291	0.8418	0.8543	0.7935	0.0000	0.0505	0.3891	0.8657
	8	0.6724	0.6891	0.9332	0.9556	0.9201	0.0000	0.0000	0.6575	0.9869
F5	**9**	0.9665	0.9530	0.9354	0.8543	0.5361	0.0000	0.0000	0.4291	0.4714
	10	0.8963	0.8330	0.7202	0.7657	0.4125	0.0000	0.0000	0.3672	0.4234
F6	**11**	0.7085	0.6951	0.3668	0.4570	0.9645	0.0291	0.0000	0.9563	0.3808
	12	0.4003	0.3766	0.2878	0.4528	0.9245	0.0000	0.0000	0.8364	0.4205
F7	**13**	0.0000	0.0291	0.7730	0.6708	0.8276	0.2687	0.1069	0.0000	0.8657
	14	0.5976	0.6342	0.8859	0.9112	0.8819	0.1819	0.1635	0.0000	0.9887
F8	**15**	0.1126	0.1071	0.5069	0.5505	0.6168	0.7840	0.9516	0.0000	0.3827
	16	0.0000	0.0000	0.3871	0.4362	0.5579	0.6627	0.8193	0.0000	0.4555
F9	**17**	0.9735	0.9786	0.5708	0.6168	0.6921	0.7074	0.9418	0.8297	0.4539
	18	0.8545	0.8374	0.4997	0.5292	0.5071	0.3519	0.9050	0.8550	0.3673
F10	**19**	0.9806	0.9823	0.4598	0.3186	0.4168	0.0632	0.3238	0.7575	0.3049
	20	0.8238	0.8017	0.3567	0.3576	0.3492	0.0023	0.2290	0.6873	0.3229
F11	**21**	0.8851	0.7575	0.0000	0.0000	0.0000	0.1375	0.2495	0.8530	0.3619
	22	0.9678	0.8675	0.1567	0.3576	0.2565	0.0000	0.3005	0.9346	0.3595
F12	**23**	0.0000	0.0000	0.0000	0.0000	0.0000	0.4683	0.8543	0.0000	0.3827
	24	0.0000	0.0000	0.0000	0.0000	0.0000	0.5962	0.9278	0.0000	0.4530
F13	**25**	0.0291	0.0000	0.5708	0.7730	0.7946	0.5071	0.3730	0.0000	0.9426
	26	0.3576	0.4368	0.8592	0.8986	0.9257	0.6795	0.4525	0.0000	0.9857
F14	**27**	0.0000	0.0000	0.6570	0.7508	0.6921	0.2126	0.4598	0.0291	0.8176
	28	0.0000	0.0000	0.7582	0.8007	0.8365	0.1987	0.2226	0.0000	0.9571
F15	**29**	0.7657	0.8063	0.5495	0.4238	0.3238	0.0632	0.2655	0.9494	0.4049
	30	0.8243	0.8556	0.4554	0.3035	0.3157	0.0000	0.2386	0.9978	0.4234
F16	**31**	0.0000	0.0000	0.8926	0.8756	0.7570	0.1071	0.1069	0.1071	0.9568
	32	0.0000	0.0000	0.8091	0.8169	0.8379	02119	0.2187	0.3234	0.9075
F17	**33**	0.9823	0.9838	0.8655	0.6921	0.6168	0.4758	0.0000	0.5951	0.5093
	34	0.8346	0.8573	0.8086	0.6557	0.6213	0.4008	0.1946	0.5057	0.4376
F18	**35**	0.9563	0.6951	0.9125	0.8845	0.6921	0.1579	0.4598	0.2126	0.5093
	36	0.8506	0.7682	0.9593	0.9687	0.5836	0.2377	0.4008	0.1840	0.4567

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3. System Function Design and Algorithm Implementation

3.1. Function Design

By discussing state monitoring and fault diagnosis methods of rotating machinery equipment, this paper combines the above three methods to design a remote fault diagnosis system for circulating water pump, with focus on the adaptation and application effects of artificial intelligence methods. The flow of the diagnostic system is shown in Figure 2.

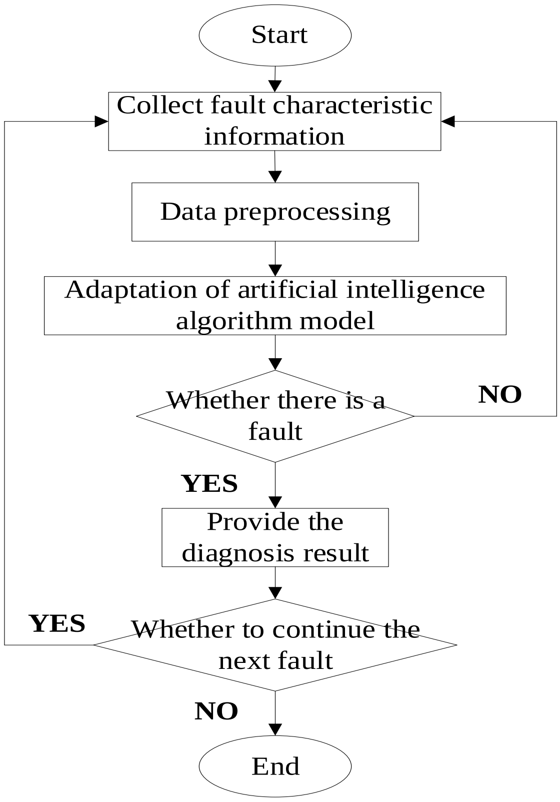

Figure 2: Fault diagnosis process

By using equipment operating data to extract fault characteristics, timely and accurately predict equipment fault based on related analysis, it is possible to accurately describe the fault phenomenon, its cause, and accurately locate the equipment fault point. The main functions are as follows:

- Open and extensible fault diagnosis knowledge base framework architecture, which can change and expand the knowledge base at any time.

- Self-learning function of the knowledge base, which can manually edit the diagnosis cases and diagnosis history records and convert them into the standard knowledge base format to learn and expand the knowledge base [6].

- Establish a fault decision tree, analyze the equipment fault mechanism according to equipment fault components, fault locations and fault phenomena to form an equipment fault tree, analyze and locate the equipment fault phenomena according to the decision tree theory, so as to facilitate the determination of the equipment fault cause and the way of overhaul when similar faults occur.

3.2. Algorithm Design

There are many indicators to evaluate the pros and cons of an artificial intelligence algorithm: generalization ability; structural complexity; robustness, that is, whether the algorithm learning parameters vary in a wide range, and whether the algorithm is good at learning. Commonly used artificial intelligence algorithms include flexible algorithm, variable learning rate algorithm, variable gradient algorithm, LM algorithm. Although these methods are all aimed at avoiding fall into local minima and increasing the convergence speed, each algorithm has its advantages and disadvantages due to different emphases. This paper will compare the learning and training of various algorithms,

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select the appropriate method in light of the characteristics of the circulating water pump, and finally apply it in the fault diagnosis of the circulating water pump.

3.2.1. Flexible Algorithm

The function Sigmoid has such characteristics: when the value of the input variable is high, its slope tends to zero, so when using the fastest descent BP method and other algorithms to train the transfer function, there will be a problem: although the weight and threshold are greatly different from the optimal value, the gradient is very small at this time, resulting in a small correction of the weight and threshold, which prolongs the training time.

The purpose of the flexible artificial intelligence algorithm is to eliminate the adverse effects of the gradient amplitude, so when modifying the weight, only the sign of the partial derivative is used, and its amplitude does not affect the weight correction. Weight change depends on the correction value that has nothing to do with the amplitude. When two consecutive iterations have consistent gradient directions, the correction value of the weight and the threshold can be multiplied by an increment factor to increase the correction value; when two consecutive iterations have opposite gradient directions, the correction value of the weight and the threshold can be multiplied by a decrement factor to reduce the correction value; when the gradient is zero, the correction value of the weight and the threshold remain unchanged; when the weight correction oscillates, the correction value will decrease. If the weight is continuously modified on the same gradient, its amplitude will definitely increase, thereby overcoming the adverse effect of the partial derivative of the gradient amplitude, that is

$$\begin{aligned}\Delta x(k+1) &= \Delta x(k+1)\cdot sign(g(k)) \\ &= \begin{cases} \Delta x(k)\cdot k_{inc}\cdot sign\big(g(k)\big)(Same\ gradient\ direction) \\ \Delta x(k)\cdot k_{dec}\cdot sign\big(g(k)\big)(Opposite\ gradient\ direction) \\ \Delta x(k)\ (g(k)\ =\ 0) \end{cases}\end{aligned} \tag{2}$$

Where: $g(k)$ is the gradient of the k th iteration; $\Delta x(k)$ is the amplitude correction value of weight or threshold of the k th iteration, the initial value $\Delta x(0)$ of which is set by the user; the increment factor k_{inc} and decrement factor k_{dec} are also set by the user.

Input the samples in Table 1 into the algorithm network, and use the flexible algorithm to train the sample set. The training effect is shown in the Figure 3:

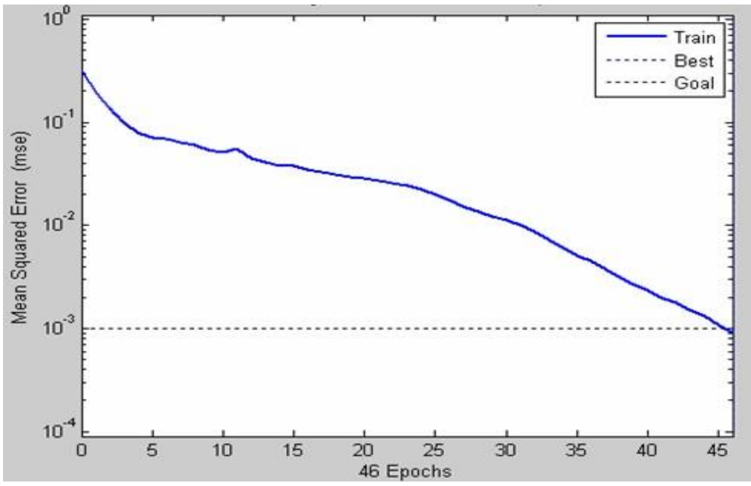

Figure 3: Training curve using elastic algorithm

3.2.2. Variable Learning Rate Algorithm

In other artificial intelligence algorithms, learning rate is a constant and remains unchanged throughout the training process. The learning algorithm performance is very sensitive to the selection of learning rate. If the learning rate is too high, the algorithm may oscillate and be unstable; if the rate is too low, the convergence speed will be slow and the training time will be long. Before training, it is not practical to choose the best learning rate. In fact, the learning rate can be changed in the training, so that the algorithm can be corrected along the error performance surface.

The gradient descent algorithm that adaptively adjusts the learning rate tries to stabilize the

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algorithm while making the learning step as large as possible during the training process. Learning rate is adjusted accordingly based on the local error surface. When the error approaches the target by decrement, it means the correction direction is correct and the step length can be increased. Therefore, if the learning rate is multiplied by the increment factor k_{inc}, it increases the learning rate; when the error increases beyond the preset value, it means correction is excessive and the step length should be reduced. Hence, if the learning rate is multiplied by the decrement factor k_{dec}, it reduces the learning rate. At the same time, the previous correction process that increases the error is removed, that is

$$\alpha(k+1)=\begin{cases} k_{inc}\alpha(k) & E(k+1)<E(k) \\ k_{dec}\alpha(k) & E(k+1)>E(k) \end{cases} \tag{3}$$

Input the samples in Table 1 into the algorithm network, and use the artificial intelligence algorithm with variable learning rate to train the sample set. The training effect is shown in the figure 4:

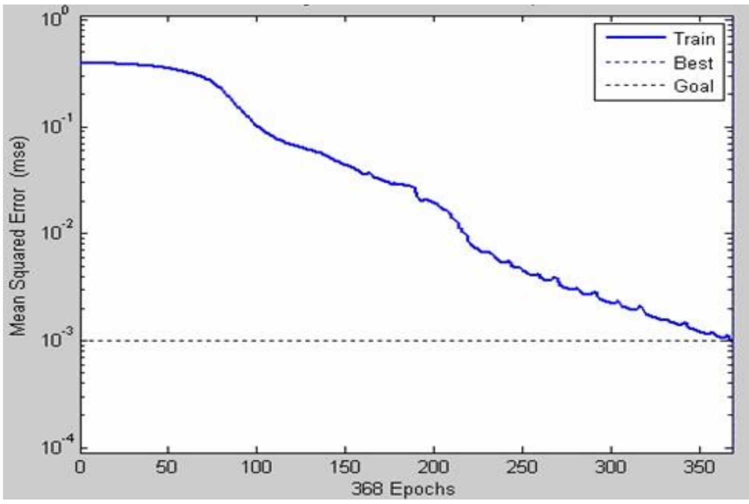

Figure 4: Training curve using a variable learning rate algorithm

3.2.3. Variable Gradient Algorithm

In the variable gradient algorithm, the search is performed along the direction of change, so that its convergence rate is faster than the convergence rate of the steepest gradient descent direction. The first iteration of all variable gradient algorithms starts the search along the steepest gradient descent direction:

$$p(0)=-g(0) \tag{4}$$

Then, the linear search to determine the best distance is performed along the direction of the current search:

$$x(k+1)=x(k)+\alpha p(k) \tag{5}$$

$$p(k)=-g(k)+\beta(k)p(k-1) \tag{6}$$

Where: $p(k)$ is the search direction of the $k+1$ th iteration. It can be seen that it is jointly determined by the gradient of the k th iteration and the search direction; the coefficient $\beta(k)$ has different calculation methods for different variable gradients. Input the samples in Table 1 into the algorithm network, and use the variable gradient algorithm to train the sample set. The training effect is shown in the figure 5:

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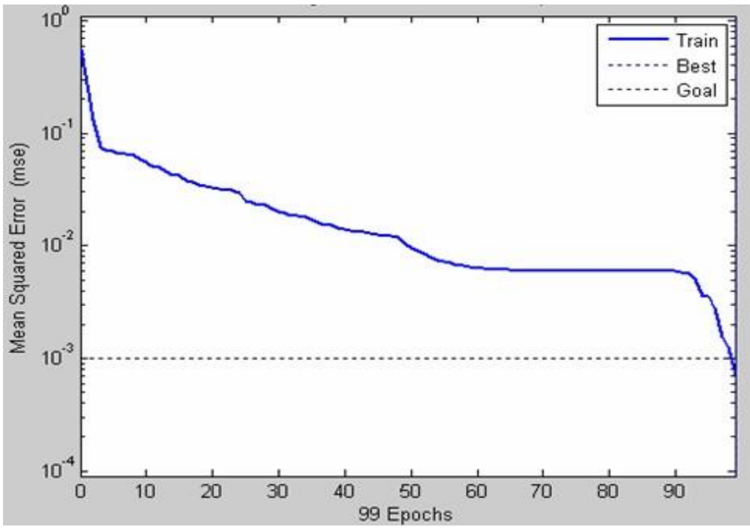

Figure 5: Training curve using variable gradient algorithm

3.2.4. LM Algorithm

LM algorithm is designed to avoid calculating the Hessian matrix when the approximate second-order training rate is corrected. When the error performance function has the form of the sum of squares error (a typical error function for training feedforward network), the Hessian matrix can be approximately expressed as

$$H = J^T J \qquad (7)$$

The calculation expression of the gradient is

$$g = J^T e \qquad (8)$$

Where: H is the Jacobi matrix containing the first derivative of the network error function against the weight and threshold, and e is the error vector of the network.

Similar to Newton's method, the LM algorithm uses the above approximate Hessian matrix for correction as follows:

$$x(k+1) = x(k) - [J^T J + \mu I]^{-1} J^T e \qquad (9)$$

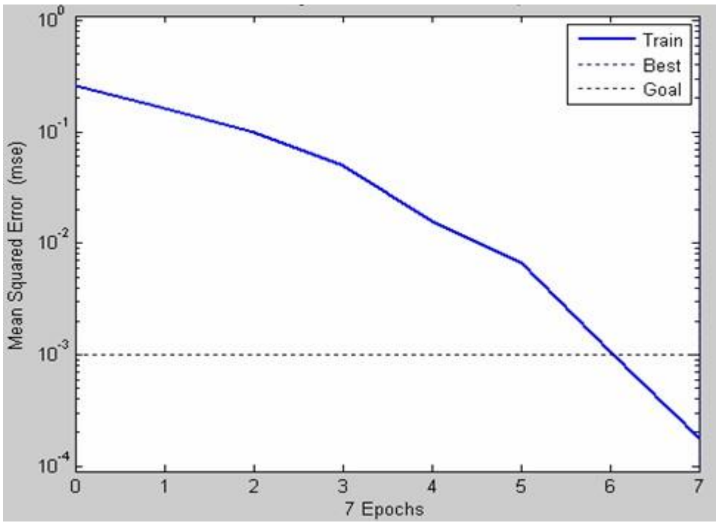

Figure 6: Training curve using LM algorithm

When the coefficient μ is 0, the above formula is Newton's method; when the coefficient value μ is high, the above formula becomes a gradient descent method with a smaller step size. Newton's method is faster and more accurate in approaching the minimum error. Therefore, the algorithm should

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approach the Newton's method as much as possible. After each successful iteration (the error performance is reduced), μ is reduced. Only when the error performance increases after tentative iterations, μ increases. In this way, the error performance in each iteration of the algorithm is always reduced.

Input the samples in Table 1 into the algorithm network, and use the LM algorithm to train the sample set. The training effect is shown in the figure 6:

3.3. Result Analysis

For a given problem, regarding which training method to use, the training speed is fast, so prediction is difficult. It depends on many factors, including the complexity of the given problem, the number of training sample sets, and the number of network weight values and thresholds, the error target, the network purpose (such as pattern recognition or function approximation), etc.

Perform data preprocessing on the above data, establish a sample set to obtain the fault symptom domain for fault diagnosis:

{0.31, 0.23, 0.14, 0.75, 0.03, 0.02, 0.05, 0.5, 0.83, 0.25, 0.75, 0.76, 0.95, 0.93, 0.75, 0.5, 0.25}

Input the above symptom domains into the algorithm network of the above four algorithms respectively, and the results obtained are as follows:

(1) Flexible algorithm:

0.9191,0.0000,0.0467,0.0510,0.0002,0.0831,0.0898,0.0055,0.0001,0.0099,0.0000,0.0000,0.0033

(2) Variable learning rate algorithm:

0.8804,0.0100,0.0000,0.0311,0.0023,0.0108,0.1327,0.0729,0.0000,0.0000,0.0003,0.0000,0.0001

(3) Variable gradient algorithm:

0.9211,0.0134,0.0024,0.0021,0.0002,0.0005,0.0005,0.0099,0.0000,0.0023,0.0000,0.0000,0.0000

(4) LM algorithm:

0.9866,0.0023,0.0323,0.0002,0.0000,0.0000,0.0227,0.0125,0.0000,0.0010,0.0034,0.0026,0.0000

It can be seen through example verification that all four algorithms can derive correct results in diagnosis. In terms of accuracy, LM algorithm has the highest accuracy, followed by the variable gradient algorithm and the flexible algorithm, while variable learning rate algorithm has the lowest accuracy. Based on comprehensive analysis of the pros and cons of various methods, this paper finally adopts the variable gradient algorithm which has relatively fast learning speed, relatively small required storage space, and high judgment accuracy.

4. Conclusion

This paper first starts from the actual needs of enterprise equipment management, collects equipment operating status and feature vectors for the platform through the equipment management system, establishes a state monitoring and fault diagnosis system based on artificial intelligence algorithms, then designs, trains and evaluates artificial intelligence algorithms. Good simulation effect is achieved. The system can comprehensively improve the equipment management level of the enterprise, extend the overhaul period of the main engine, greatly reduce emergency repair work, gradually realize real intelligent maintenance of the main equipment and important auxiliary equipment of the energy system, and finally comprehensively improve the reliability of the main and auxiliary equipment, thus greatly reducing equipment operation and maintenance costs and labor intensity.

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