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An Improved BP Neural Network Algorithm for Prediction of Roadway Support

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***Abstract*—Based on the engineering practice and the research and analysis of the knowledge in the field of roadway support, the paper puts forward to use an improved BP neural network to study the supporting types by the investigation, and obtained the related factors of the supporting types of the mining roadway and the successful reinforcement cases of the roadway. The proposed algorithm is applied to the prediction of coal roadway support parameters, and the main influencing factors of coal roadway support design are determined. From the typical engineering cases of roadway support collected on site as neural network training samples, the forecasting model of support parameters is established. Through the experimental data and simulation results, it can be seen that both the error convergence process and results of convergence speed, convergence accuracy and support types are ideal, the prediction error is within the allowable range, and the prediction accuracy is high, which verifies the reliability of this method and provides a new research idea and good application value for the study of support types of mining roadway.**

***Keywords*—BP neural network, roadway support, sample training, network learning parameters, principal component analysis, LM algorithm**

I. INTRODUCTION

THE pre-mining roadway is the most important mining engineering of non pillar stope, and it is also an underground engineering with poor surrounding rock environment [1-3]. With the development of underground engineering, the surrounding rock is continuously impacted by vibration and often fails [4]. In order to ensure the safety of underground engineering and normal mining activities, the surrounding rock must be supported and reinforced.

Coal roadway support is the key link of mine production and construction [5-6]. It is neither scientific nor safe to determine the support scheme only by simple engineering analogy of field technicians. It is necessary to use the rapid development of artificial intelligence algorithm in recent years to make support scheme decision. At present, although there are many kinds of research methods on the types of roadway support, there are many factors affecting the types of support, which are complex and interact with each other, and each factor has uncertainty. The traditional method has high requirements for construction technology, and the general technical level is not ideal[7]. The support design of coal mine roadway with traditional BP neural network has achieved good results [8-10]. However, the complex geological conditions and production conditions of coal roadway make it difficult to select the input parameters. The inherent defects also make the prediction stability of support parameters poor and the actual effect poor.

In view of the above problems, the proposed algorithm is used to predict the support parameters of coal roadway by analyzing the typical case data of support engineering in the mining area on the basis of the investigation and analysis of the stability of the mining gateway in iron mine and the study of the support evaluation method. The structural parameters of prediction model are determined, and the support parameters are predicted on the basis of analyzing the key factors affecting the support design of roadway.

II. PRINCIPLE BP NEURAL NETWORK

A. Basic Principle of BP Neural Network

BP neural network algorithm consists of two parts [11-13], the input layer and the output layer through the established learning rules, and verify the calculation effect compared with the set error, which is the forward propagation process of the data. Only through the training of learning samples in the database, some rules between input and output can be found out. The algorithm can analyze the error size. If the accuracy effect is not satisfied, the error is fed to the input layer from the output layer[14]. After iterative calculation, the final result is obtained after many times of operation, which is reflected in the form of the weights and thresholds of each layer. This is the reverse transfer process of the error, and the training is completed through the above two steps.

In the whole design of BP neural network model, its basic processing unit includes input layer, output layer, hidden layer, transfer function and training function. Combined with the case of coal mine roadway, the model is designed. However, BP neural network still has some shortcomings[15], which are described as follows. BP neural network can sink into local

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extremum and converge to local minimum [16-17]. The objective function of BP neural network optimization is complex, and the initial weight, threshold and the best fitting position are difficult to determine. Especially when the output is close to 0 or 1, the training process is more likely to fail. The approximation of network model has a great relationship with the test sample set used. Different samples may lead to different approximation results.

Back propagation (BP) network is a kind of multilayer feedforward neural network proposed by McCelland et al. Its learning is divided into two stages: one is the forward propagation stage of the signal, the sample data is input to the input layer, and the middle is processed by each hidden layer. The processed results are transmitted to the output layer, and the output layer outputs the final results. The other is the error back propagation. The error between the expected output and the actual output is transmitted to the input layer through the hidden layer in a certain way. In the process of transmission, the error is divided equally to each unit in the middle. Each neuron obtains its own error and modifies its own weight according to the error. The process of weight modification is the process of neural network learning. The process continues until the number of learning times set before the training of sample data is reached, or the output error reaches the allowable range. Its structure is shown in Figure 1, which is composed of input layer, hidden layer and output layer.

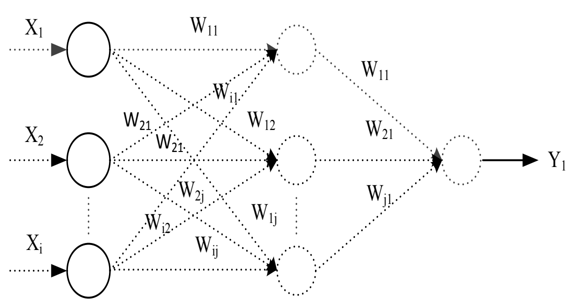

Fig. 1. The structure of BP neural network

In Figure 1, X_1, X_2, ..., X_i is the input, Y_1 is the output, W_{ij} is the weight from the input layer to the hidden layer, W_{jk} is the weight from the hidden layer to the output layer.

B. Algorithm Steps of BP Neural Network

Figure 2 is the flow chart of BP neural network algorithm.

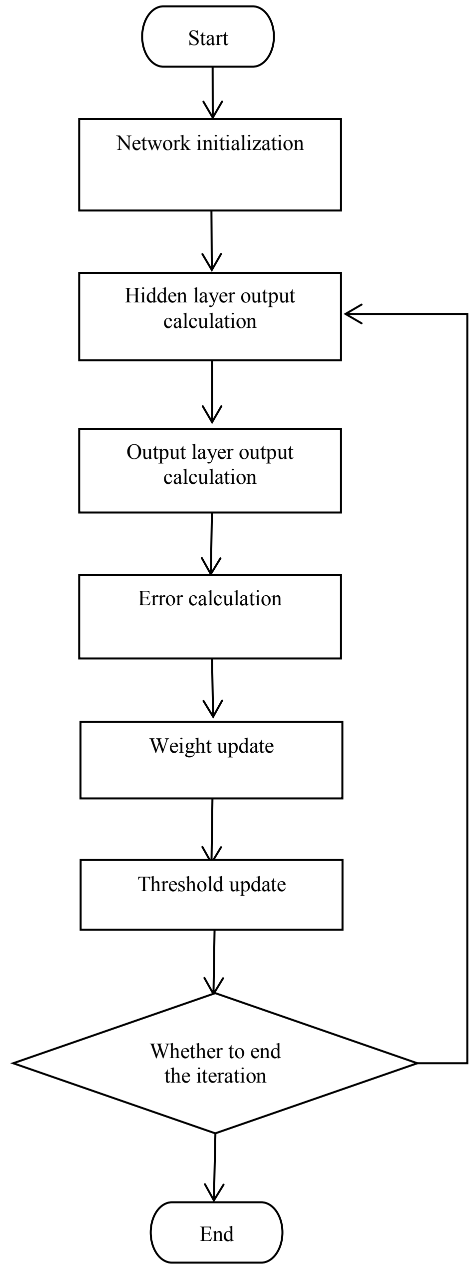

Fig. 2. The flow chart of BP network algorithm

BP neural network algorithm steps are as follows.

Step 1. Network initialization.

Step 2. Calculate the output of the hidden layer.

Let the hidden layer and the output layer adopt *sigmoid* function, that is,

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

$$H_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - \theta_j\right) \tag{2}$$

Step 3. Calculate the output of the output layer.

$$O_k = \sum_{j=1}^{q} H_j w_{jk} - b_k \tag{3}$$

Step 4. Calculation error.

According to the actual output and the expected output, the error e_k and mean square error E_k are calculated

$$e_k = Y_k - Q_k \tag{4}$$

$$E_k = \frac{1}{2}\sum_{j=1}^{l}(Q_k - Y_k)^2 \tag{5}$$

Step 5. Update weights.

$$w_{ih} = w_{ih} + \eta H_j(1-H_j)x_i\sum_{k=1}^{n} w_{hi}e_k \tag{6}$$

$$w_{hj} = w_{hj} + \eta H_j e_k \tag{7}$$

Where η is the learning rate.

Step 6. Update threshold.

$$\theta_j = \theta_j + \eta H_j(1-H_j)\sum_{k=1}^{l} w_{jk}e_k \tag{8}$$

$$\gamma_h = \gamma_h + e_h \tag{9}$$

Step 7. It is judged whether it is within the allowable range according to the output result error. If it is, the algorithm ends, otherwise it jumps to step 2.

C. Shortcomings of BP Neural Network

BP neural network algorithm can approximate any nonlinear function with any precision, but it also has some shortcomings.

(1) Because BP neural network algorithm is a local search method, and it solves a nonlinear problem, the network connection weight is adjusted along the direction of local improvement in the training process, so it is easy to fall into local minimum. In addition, with different initial weights, the network converges to different local minima in the training process, which makes the performance of the network unstable.

(2) There is no unified theoretical guidance for the construction of the initial network structure, which is generally set according to experience, and then adjusted according to the output results, which will directly affect the approximation ability and generalization ability of the network, thus affecting the final effect of the algorithm.

(3) The learning ability and generalization ability of BP neural network are closely related to the selection of samples. If the selected samples are contradictory, redundant and unrepresentative, the training of BP neural network is difficult to achieve the desired effect.

III. Principles of Establishment for Roadway Support Model

The input and output layer nodes are determined as follows. According to the actual situation of coal mine roadway, seven input layer node factors of neural network algorithm are determined: roof surrounding rock strength, floor surrounding rock strength, two sides surrounding rock strength, first caving distance of direct roof, buried depth, roadway clear width and roadway clear height. In the case of bolt support, five output layer node factors can be determined: bolt length, bolt diameter, bolt spacing, bolt row spacing and support type. The calculation is carried out twice for the accuracy of data prediction. The sample data of two layers are collected, analyzed and summarized, and the typical roadway database is established.

The design of the hidden layer is as follows. The number of hidden layers and nodes is directly related to the prediction results. However, the increase of the number of hidden layers will also lead to the increase of training time and the complexity of the determination of node parameters, that is, too many hidden layer nodes will increase the training time, too few will cause too much error. At present, some formulas for the number of hidden layer nodes are not very accurate, so it needs to be determined by combining the designer's experience and reference formula.

The initial value includes the weights and thresholds of each layer, which has a great influence on whether the neural network can achieve the global optimization and the allowable error. In the first training, the weights and thresholds are generally random values and limited in the range of (0,1). At the same time, the input and output samples are normalized to make the data structure more reasonable and avoid excessive error.

Based on the relevant research literature and many simulation operations, the input layer is determined to be logarithmic function and the output layer is determined to be linear function. The combination of the two functions can make the algorithm approach any form of nonlinear function mapping.

IV. Improvement of BP Neural Network algorithm

Due to its inherent defects, the standard BP algorithm still has some shortcomings in the accuracy of support parameter prediction [18]. Generally, the application of BP algorithm is based on the improvement of its training function. In order to overcome the above defects, this paper proposes an improved BP neural network algorithm with early termination judgement and Levenberg-Marquardt (LM) [19]. Firstly, principal component analysis(PCA) is used to find out the attributes with high correlation and reduce the processing dimension of data set, so as to solve the problem of slow convergence and over-dependence of test samples. Secondly, the neural network is trained by early termination judgement, so as to find the best training times and solve the problem of over-adaptation.

A. Principal Component Analysis

Principal component analysis (PCA) is a dimensionality reduction method [20]. Its essence is to transform multiple irrelevant attributes in the original sample set into a set of irrelevant variables that can replace the original indicators, and select variables with more original information as the principal components of the analysis data. The greatest advantage of this method is to find the correlation between attributes and make the dimension decline with attributes set on the premise of minimizing the loss of information as much as possible. Specific implementation steps are described as follows.

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Step 1. Normalizing data sets.

Step 2. Obtaining the correlation coefficient matrix of all attributes. The correlation coefficients r_{ij} of the attributes in column i and column j are shown in Equation (1).

$$r_{ij} = \frac{\sum_{k=1}^{n}(y_{ki}-y_i)(y_{kj}-y_j)}{\sqrt{\sum_{k=1}^{n}(y_{ki}-y_i)^2\sum_{k=1}^{n}(y_{kj}-y_j)^2}} \tag{1}$$

Where y_{ki} represents the element in the k-th row and the i-th column of the matrix, n is the row number, and y_j is the mean of the i-th column.

Step 3. Calculating the eigenvalues of all attributes $\lambda_i(i=1,2...,p)$ and the corresponding eigenvectors $e_i=(\alpha_{1i},\alpha_{2i},....\partial_{pi})(i=1,2,...,p)$.

B. Early Termination Judgment

Early termination judgement can improve the generalization ability of network, and it is suitable for training functions. The original data can be divided into three sample sets. The training function carries out network modeling for three sample sets at the same time, in which the training sample set has the function of adjusting the weights and thresholds of the network and calculating the training error. When the validation error increases with the decrease of the training sample error, the network enters the over-training stage. When it reaches a certain level, it will terminate the training ahead of time and return the network object with the minimum validation error. The test error generated by the test sample set is for appraise the properties of the network. If the number of training steps returned when the test error and the verification error are minimum is very different, it shows that the partition of the sample set is unreasonable, and the reference value of the network training results is not significant.

C. The Main Idea of the Improved BP Neural Network Algorithm

The improved BP neural network algorithm can be divided into two processes. Firstly, PCA is used to reduce the dimension of the monitored attributes, further reduce the amount of redundant data, and improve the correlation between attributes. Secondly, through the early termination judgement, three sample sets are reasonably allocated, and the BP neural network training is carried out.

The flow of the improved BP neural network algorithm is described as follows.

Step1. PCA algorithm is used to normalize the original sample set, and the correlation coefficient matrix, eigenvalues and corresponding eigenvectors are calculated.

Step2. The contribution rate and cumulative contribution rate of each component are calculated. Generally, the components with cumulative contribution rates of 80% - 90% are selected as the new sample data set.

Step3. The new sample set is randomly divided into training sample set, validation sample set and test sample set according to the proportion of 80%, 40% and 20%. The data sets are selected in the above way, which can reduce the particularity and dependence of samples and enhance the training ability of the network.

Step4. The number of nodes in input layer and output layer is predetermined, and the range of nodes in hide layer is calculated.

Step 5. The training function is used to train the three sample sets with the method of early termination judgment. The errors caused by the sample sets are compared, and the optimal number of hide layer nodes and iteration times are found. Finally, the BP neural network model is determined.

D. LM Algorithm for Sample Training of Roadway Support

LM algorithm has fast operation speed and high accuracy, and is especially suitable for medium level neural networks. According to the above principles and advantages, LM algorithm can improve the BP neural network based on the prediction of coal roadway support scheme.

When the coal property is soft coal, the following formula is used to pretreat the strength of roadway roof, two sides and floor.

$$W=\exp\left[-\sigma\left(\frac{B-B_0/3}{B_0}\right)^2\right] \tag{3}$$

where W is width processing converted data, B is initial width of coal wall, B_0 is width of coal rib after treatment, and σ is coal property coefficient, $\sigma=2.6$.

B_0 is calculated according to the following formula

$$B_0=15.43+0.098H \tag{4}$$

where H is buried depth of roadway.

When the coal property is medium hard, the following formula is used to pretreat the strength of roadway roof, two sides and floor.

$$W=\exp\left[-\sigma\left(\frac{B-B_0/4}{B_0}\right)^2\right] \tag{5}$$

where $\sigma=3.6$.

B_0 is calculated according to the following formula

$$B_0=8.43+0.046H \tag{6}$$

When the coal is hard, the following formula is used to pretreat the strength of roadway roof, two sides and floor.

$$W=0.3\exp\left[-\sigma\left(\frac{B-B_0/4}{B_0}\right)^2\right] \tag{7}$$

where $\sigma=3.6$.

B_0 is calculated according to the following formula

$$B_0=5.34+0.032H \tag{8}$$

This algorithm model can be operated only when the data columns are equal. Therefore, for the original data, in the case of its data processing transpose, can ensure the accuracy of the operation process. At the same time, due to the different dimension and magnitude of each index of the data, if the original sample data is used directly, the error will be too large due to the different size of the data, which will affect the training effect.

V. DEFINITION OF LEARNING SAMPLES

A. Definition of Learning Samples

The learning samples of the network are from the pre mining roadways at - 316 m level and - 330 m level. The lithology of the roadways is determined according to the geological logging, and the uniaxial compressive strength is determined. The stress environment of the roadways is determined according to the mining conditions of the corresponding upper layer. The stress reduction area is when the upper mining is better, and the stress concentration area is when the mining is worse, According to the actual acceptance diagram of roadway, combined with the layered mining blasting diagram, the existence time of roadway can be determined, and the service life can be defined in the different range. The results show that the influence of underground water is serious when the roadway drips out of water. The occurrence of the main weak structural plane has different combination relationship with the roadway axis, which has different influence on the stability of the roadway. When the angle between the strike of the structural plane and the axial direction of the roadway is greater than 60 ° and the dip angle of the structural plane is greater than 75 °.

B. Sample Statistical Analysis

Among the input and output factors, except for the uniaxial compressive strength, all the other factors are qualitative factors. The results are shown as Table 1.

Table 1. The lithology statistics of samples

Lithology	Number	Lithology	Number
Diorite	5	Anhydrite	3
Granite	5	Massive Lean Magnetite	7
Skarn	7	Massive Magnetite	8
Quartz Granite	5	Fault Fracture Zone	7
Marble	4	Fine Ore	2

According to the statistical results in the table, the distribution of factors in the sample is not uniform, and some even differ greatly, especially in lithology. Therefore, in the prediction of network behavior verification, we must consider the selection of prediction samples, and can not randomly extract some samples for prediction.

VI. MODEL TRAINING AND JUDGMENT

In order to obtain the feasibility for predicting the support form of underground roadway, and to provide theoretical basis for the support type of underground roadway in iron mine, Matlab is used for training and prediction analysis. From 50 samples, 35 samples are selected as training samples, and 15 samples are selected as prediction samples.

A. Quantification of Input and Output Factors

In order to reasonably determine a certain value in the learning samples, it is determined in the range of (0,1). For a certain factor of uniaxial compressive strength, the data are normalized by formula (10).

$$x' = \frac{0.6}{(x_{\max} - x_{\min})}(x - x_{\min}) + 0.3 \qquad (10)$$

x' is the normalized numerial number, $x_{\max}$ is the maximum numerial number of the corresponding factors, $x_{\min}$ is the minimum numerial number of the corresponding factor, x is the actual numerial number of the relevant factors.

In order to ensure the expansibility of quantification, the maximum numerial number is 86.85 MPa, and the minimum numerial number is only 0.15 MPa in the sample table. In the process of normalization, $x_{\max}$ = 87 MPa, $x_{\min}$ = 0.1 MPa.

For qualitative factors in Table 2, the treatment and quantification are shown in Table 3. Support type are Ⅰ8, Ⅱ7, Ⅲ13, Ⅳ7, Ⅴ7, Ⅵ8.

Table 2. Statistics of other qualitative factors in the sample

Factor name	Factor subclasses and statistics		
Stress environment	Concentration area 12	Protolith area 20	Reduction zone14
Years of service	One year 10	Two years 16	Three years 20
Service function	Cutting Lane 13	Route 18	Combined Ways 22
Groundwater impact	Commonly 20	Nothing serious 15	Serious 13
Occurrence of structural plane	Commonly 19	Nothing serious 20	Serious 15

Table 3. Normalization value of qualitative factors

Factor name	Factor subclasses and statistics		
Stress environment	Concentration area 0.8	Protolith area 0.4	Reduction zone 0.2
Years of service	One year 0.2	Two years 0.4	Three years 0.8
Service function	Cutting Lane 0.2	Route 0.4	Combined Ways 0.8
Groundwater impact	Commonly 0.2	Nothing serious 0.4	Serious 0.8
Occurrence of structural plane	Commonly 0.2	Nothing serious 0.4	Serious 0.8

In order to have an obvious classification method for the prediction results, the following provisions are made here, as shown in Table 4.

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Table 4. Support type corresponding to predicted value

Predictive value *a*	Corresponding support type
$0<a<0.1$	VI
$0.1<a<0.25$	V
$0.25<a<0.4$	IV
$0.4<a<0.6$	III
$0.6<a<0.8$	II
$0.8<a<1.0$	I

B. Network Learning Parameters

The determination principle of network learning parameters is as follows.

Step1. Network Nodes: Hidden layer nodes are selected according to experience, which is generally set as 75% of the number of input layer nodes. If there are 7 nodes of input layer and 1 node of output layer, then the hidden layer can be temporarily set as 5 nodes, which constitutes a 7-5-1 BP neural network model. In the system training, the actual hidden layer nodes 4, 5, 6 are compared, and finally determine the most reasonable network structure.

Step2. Determination of initial weight: initial weight is a group of values that should not be completely equal. It has been proved that they will always remain equal in the learning process, even if there is a set of unequal weights which make the system error smaller. Therefore, a random generator program is designed as the initial weights of the network.

Step3. Training rate: The larger the training rate is, the better. The traditional default value of learning rate is 0.1 or 0.01. The default value of 0.01 is usually suitable for standard multilayer neural networks.

Step4. Dynamic parameters: the selection of dynamic coefficient is also empirical, generally 0.6 ~ 0.8. In the case of different image size proportion and different training parameter size proportion, 0 value is inserted into the predicted value according to the training parameter size proportion so as to achieve the original training parameter proportion. When the picture size is smaller than the training parameter size, the average value is added to be inserted in the row and column of the predicted value to reach the original training parameter size. When the size of the picture is larger than the size of the training parameter, the residual value of the original training parameter size is obtained, and the predicted value is divided to the position of the last obtained value, so as to achieve the size of the original training parameter. According to this principle, the input parameters of the neural network are variable.

Step5. Allowable error is generally 0.001 ~ 0.00001. When the error of two iterations is less than this value, the system ends the iterative calculation and gives the result.

Step6. Iteration times is generally 1000 times. Because the neural network calculation can not guarantee the convergence of the iterative results under various parameter configurations, when the iterative results do not converge, the maximum number of iterations is allowed.

Step7. Sigmoid parameter: this parameter adjusts the form of neuron excitation function, generally between 0.9 and 1.0.

Table 5 shows the learning parameters in the process of network learning.

Table 5. Network learning parameters

Parameter name	Parameter value
Nodes in input layer	6
Nodes in output layer	1
Nodes in hidden layers	2
Nodes in the first layer of hidden layer	6
Nodes in the second layer of hidden layer	7
Learning rate	0.1
Learning impulse	0.2
Learning expectation error	0.08

C. Online Learning Training Results

The network simulation of the sample set is carried out. Taking the validation sample set as an example, the results of network training are shown in Fig.3. The real line is the actual normalized validation sample, and the dotted line is the predicted value of the network. Fig.4 shows the result graph of BP network training on the original data set.

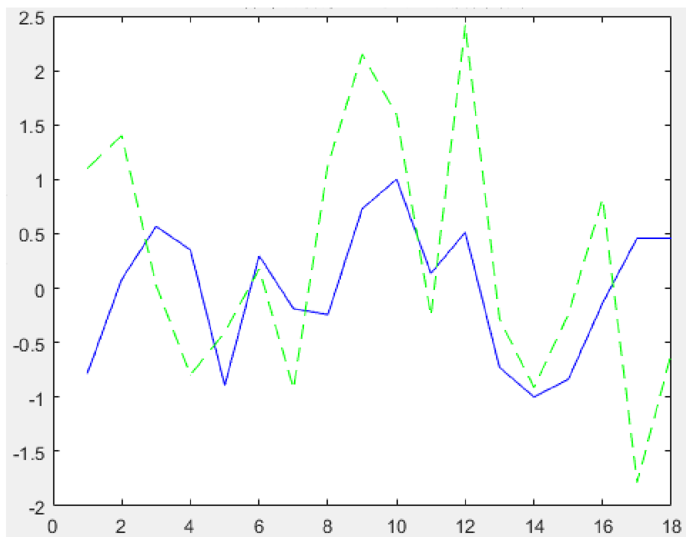

Figure 3. Training results of improved BP algorithm

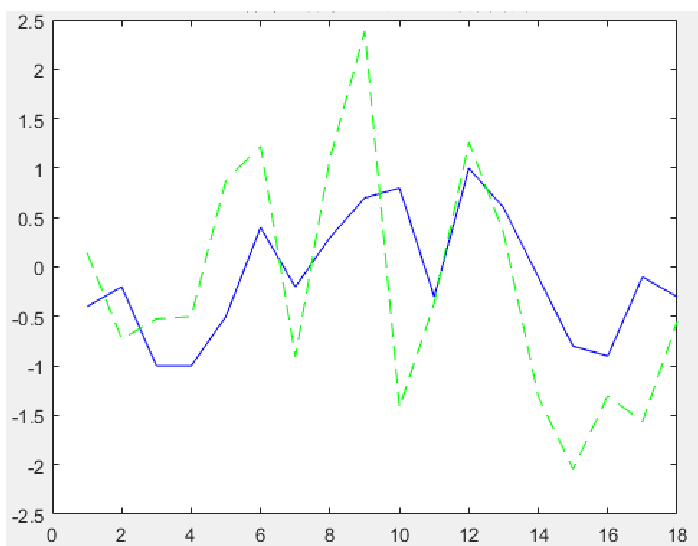

Figure 4. Training results of traditional BP algorithm

The correlation errors between the two methods are shown in Table 6. The smaller the mean square error is, the more accurately the prediction model can describe the experimental data.

Table 6. Computational errors of two methods

Algorithms	mean square error	Mean absolute error
Improved BP	1.0028	0.8229
Traditional BP	1.2989	0.9615

VII. FORECAST RESULTS AND ANALYSIS

Using the learning results of the above 45 samples, the prediction analysis is carried out according to the pre selected prediction samples, and the results are shown in Table 7.

Table 7. The prediction results are compared with the actual situation

Sample number	5	9	18	25	36	42
Expected output	0.930	0.870	0.480	0.660	0.390	0.710
Support type	VI	I	VI	II	V	III
Actual output	0.941	0.861	0.462	0.630	0.364	0.232
error	-0.011	0.009	0.018	0.030	0.026	0.478
Accuracy	good	good	good	good	good	poor

It can be seen from Table 7 that among the six predicted samples, except for sample 50, the prediction results of the other five samples are accurate, with an accuracy rate of 82.67%. This shows that the improved BP neural network is feasible to predict the support type of the mining gateway, which provides a theoretical basis for accurately predicting the support type of the mining gateway in iron mine.

VIII. CONCLUSION

After the key factors affecting the bolt support design of coal roadway, it is concluded that the input node is 7 index data, and the output node is 5 index data, including bolt length, bolt diameter, bolt spacing, bolt row spacing and support type. Through the learning of the network learning samples and the prediction results of the support types, it can be seen that the prediction results of the learning sample error convergence process, convergence speed, convergence accuracy and support types are ideal, and the prediction accuracy is high, It provides a new research idea for the study of the support type of underground mining roadway.

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