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Prediction of Mine Earthquake Intensity Based on BP Neural Network

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Abstract

In order to accurately predict mine earthquake intensity, this paper designs a mine earthquake intensity prediction model based on BP neural network, which takes 9 monitoring index data as input and earthquake magnitude as output. Through 47 monitoring instances and 200 iterations, the average absolute error of training prediction is 0.286. The prediction results show that the model has high prediction accuracy and reliable results.

Keywords

BP neural network; mine earthquake intensity; coal mine risk prediction; mine accident hazards.

1. Introduction

The safety of coal mines has become a top priority for the sustainable development of coal mines. Once major accidents such as water, fire, gas, coal dust and roofs occur in coal mines, it will not only bring serious losses to miners' lives and properties, but also cause severe damage. social influence. The monitoring, identification, prediction and early warning research of major accident hazards is highlighted as a major issue of safety production that needs to be solved urgently at present [ ]. In this regard, many scholars have done a lot of work. Meng Xiangning [ ] proposed an improved particle swarm least squares support vector machine (MPSO-LSSVM) mine wind temperature prediction model; Theoretical, respectively predicted the mine gas emission; Lv Pengfei [ ] et al. constructed a rockburst risk classification prediction method based on the PSO-LSSVM method, and predicted the working face example. The above scholars have all made significant contributions to the prediction of major accident hazards.

However, in recent years, dynamic disasters such as mine earthquakes have occurred frequently. In addition to inducing underground shocks, strong mine earthquakes can also cause vibration damage to buildings (structures). [ ] Therefore, predicting the mine earthquake intensity is of great significance to the safety of coal mine production, but few scholars monitor and predict this accident risk source. Therefore, this paper uses the BP neural network to predict the mine earthquake intensity.Organization of the Text

2. BP Neural Network Prediction ModelIntroduction

The multiple-layer feedforward network (BP network for short) based on the error back propagation algorithm is one of the most widely used and successful networks at present. The structure of BP neural network is shown in Figure 1:

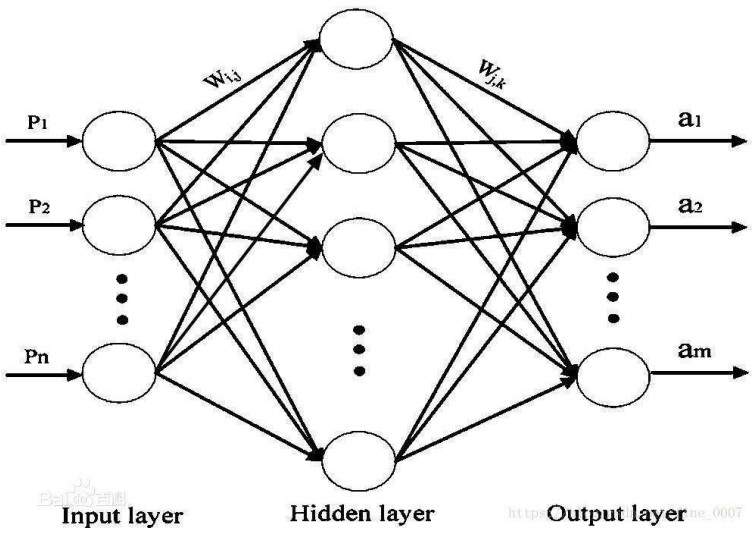

Figure 1: BP neural network

2.1. Forward-propagation

Forward propagation is mainly about the understanding of the activation function. For the jth neuron in the lth layer of the network, it will receive signals from all neurons in the l−1th layer, namely:

$$z_j^{(l)} = \sum_{i=1}^{m_{l-1}} \omega_{ji} a_i^{(l-1)} + a_0^{(l-1)} \tag{1}$$

For multi-classification problems, the output of the kth neuron in the output layer of the network can be expressed as:

$$y_k = a_k^{(l+1)} = h(z_j) = h\left(\sum_{j=0}^{m_l} \omega_{kj} a_j^{(l)}\right) \tag{2}$$

The activation function in BP neural network usually takes the sigmoid function or the tanh function

2.2. Cost Function

The output value of the BP network under one sample can be obtained from the formula in Section 1.1. We define the sum-of-square error function as follows:

$$E_p = \sum_{k=1}^{m_{l+1}} \frac{1}{2} (y_k - t_k)^2 \tag{3}$$

With all sample inputs, the total error of the network is:

$$E_n \sum_{p=1}^{n} E_p \tag{4}$$

2.3. Back-propagation

This is the core part of the BP neural network. The error is back-propagated from the output layer layer by layer, and the weights of each layer are updated by the gradient descent algorithm, namely:

$$\omega := \omega - \eta \nabla E_p(\omega) \tag{5}$$

In the above formula, η is the step size of each update, and ∇Ep(w) is the partial derivative of the output deviation under the input of the pth sample to the weight of a certain layer, which means that the parameters are updated once for each input sample.

3. Example Analysis of Mine Earthquake Intensity Prediction

3.1. Experimental data

Referring to previous studies, this paper selects 47 sets of data in the literature [ ] for analysis, where X1 is the detection value of the deep hole stress in the upper level road (Mpa); X2 is the detection value of the shallow hole in the upper level road (Mpa); X3 is the lower level road. The detection value of the deep hole stress in the roadway (Mpa); X4 is the detection value of the shallow hole stress in the lower level roadway (Mpa); X5 is the monitoring pulverized coal amount in the upper level roadway and the lower side (Kg/m); X6 is the monitoring coal powder in the upper level roadway and the lower side. Weight (Kg/m); X7 is the maximum support resistance in the entire working face (Mpa); X8 is the average support resistance in the entire working face (M/pa); X9 is whether there is a process nearby when the mine earthquake comes (cutting Coal, maintenance, etc.), if there is a process, it is recorded as 1, and if there is no process, it is recorded as 0; Y is the magnitude, and some sample data are shown in Table 1.

Table 1: Partial sample data

Serial number	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	Y
1	5.8	5	4.3	5.3	1.91	1.75	37.5	14.3	0	0.7
2	6	6.6	5.2	3.8	1.71	1.74	36.8	16.8	0	0.7
3	7.7	7.8	6.6	7.4	1.97	1.82	37	18.4	0	1
4	6.8	7.4	6.2	4.8	2.02	1.82	39.9	20.8	0	1.2
5	7.1	7.6	6.4	6.4	1.87	1.82	37.8	20.9	0	1
6	6.9	7.9	6.6	6.8	2.07	1.82	39.7	20	0	1.2
7	7.4	7.3	4.7	7.9	2.03	1.82	47.4	18.1	0	1
8	7.4	7.3	4.7	7.9	2.02	1.82	49.5	21.3	0	1.6
9	4.2	6.4	4.7	7.6	1.83	1.82	34.7	15.3	0	1.1
10	5.8	6.8	4.9	4.6	1.72	1.82	38.3	16.1	1	1.2
11	4.3	7.3	5.7	6.5	1.71	1.82	37.1	21.3	1	1.6
12	4.4	7.9	4.1	6.2	1.88	1.82	39.7	21.3	0	1
13	4.6	7.5	4.1	4.6	1.79	1.82	39.5	17.4	0	0.5
14	4.6	6.8	4.2	4.7	1.89	1.71	38.3	23.2	0	1
15	4.8	7	4.2	4.9	1.81	1.75	38	23.2	0	1

3.2. Feature data normalization

In order to speed up the speed of gradient descent to find the optimal solution, it is necessary to normalize the sample data, and scale the values of the numerical features in the training set to be between 0 and 1. The formula is as follows:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{mix}} \tag{6}$$

Among them, X is the normalized data, X_{min} is the smallest data in the sample, X_{max} is the largest data in the sample, and X_{norm} is the normalized value of feature X.

3.3. Evaluation of prediction results

Model training was performed on 47 sets of data, with a total of 200 iterations. After the training is completed, the random scramble tool is used to scramble the original sequence and return a new scrambled data sequence with scrambled values to prevent false training output in the original order. Finally, three groups were randomly selected from the 47 groups of data for prediction, and the prediction results are shown in Table 2.

Table 1: forecast result

serial number	Predictive value	actual value	absolute error	Relative error/%
10	1.19	1.20	-0.01	-0.83
33	0.77	0.70	0.07	10
42	0.83	0.90	-0.07	-7.78

Figure 2 is a histogram of forecast errors. It can be seen that most of the forecasts are accurate:

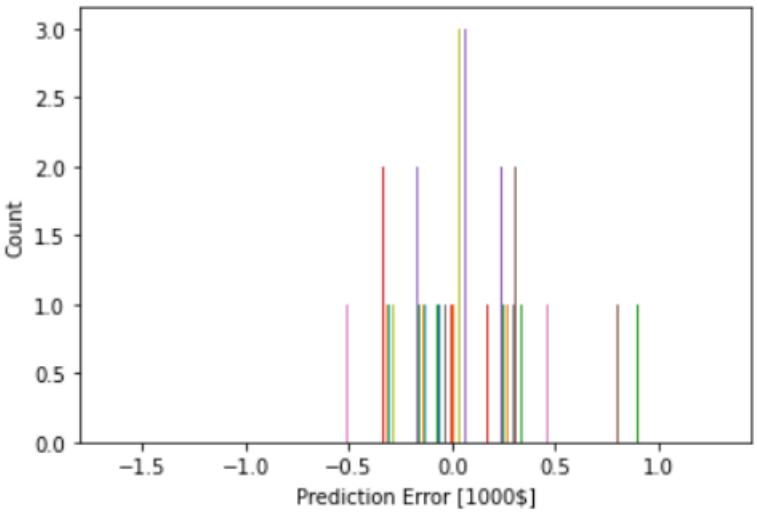

Figure 2: Forecast error histogram

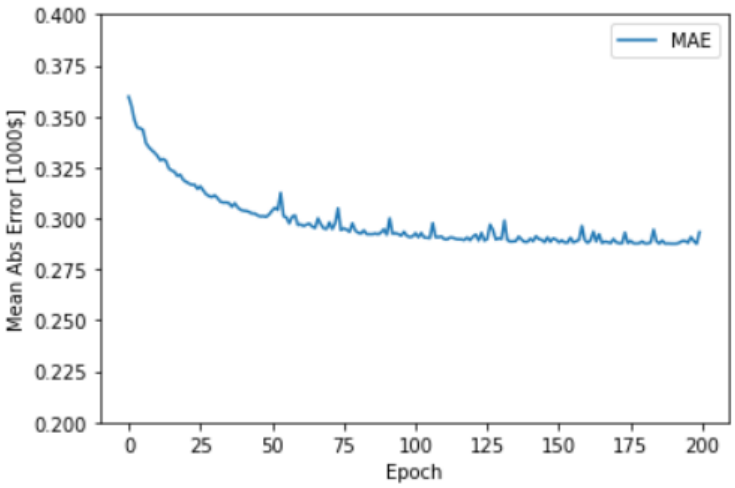

Figure 3: mean absolute error of forecast

Figure 3 shows the change trend of the mean absolute error of the predicted value: MAE (Mean Absolute Error). It can be seen that after more than ten rounds of training, it tends to decrease and finally becomes almost stable.

4. Conclusion

1. Through 47 monitoring instances and 200 iterations, the average absolute error of training prediction is 0.286. The prediction results show that the model has high prediction accuracy and reliable results.

2. The prediction of mine earthquake, which is a dangerous source of accidents, is solved through BP neural network, which has reference value for coal mine safety production.

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