HONGJUN GUO
MING JI
MENG ZHANG
KUN ZHANG
HUIQIN WANG
and
AOXIANG LIANG

Application of BP neural network in the prediction of periodic weighting

Based on the theory of BP neural network, the monitored data of the cyclic end resistance of hydraulic support in 02178 working face of Huopu mine is trained. Through analyzing the errors produced by the different nodes of network hidden layer, the periodic weighting prediction model whose network structure is 4-12-1 is built. After field monitoring, the 5th weighting is predicted. And the results showed that the average periodic weighting step is 9.1 m, and the influence range covers 1.53 m, and the average dynamic load coefficient is 1.28. Evidently, the output values of network are basically consistent with the monitored data. Therefore, these predicted data can provide a theoretical basis for supporting design and safety production of roadway with the same conditions.

Abstract: *BP neural network; periodic weighting; pressure prediction; roof control*

1. Introduction

Mining is a huge and complicated underground production system, and it is influenced by geology, hydrology, tectonics, stress, mining conditions and many unknown coefficients. Therefore, safety is the basis and premise of mining. However, the mine accidents occurred frequently. According to the survey and statistics, the accident rate of roof is highest in coal mine eight accidents (roof, gas, machinery and electric, transportation, blasting, flood, fire and others). Roof accidents accounts for more than 50% of the total number of accidents, and 50% of them occurred in the working face [1-4]. In order to reduce the damage of roof accidents, a lot of measures of pressure monitoring are taken in the process of mining and excavating in each mine. And also a large amount of pressure monitoring data are obtained, which plays a guiding and decision-making role for mine roof management and control. However, the study of monitoring data is merely simple statistical analysis, which is lack of scientificity and systematicness.

Messrs. Hongjun Guo, Ming Ji, Meng Zhang, Kun Zhang, Huiqin Wang and Aoxiang Liang, Key Laboratory of Deep Coal Resource Mining, Ministry of Education of China; School of Mines; China University of Mining & Technology, Xuzhou, 221116, China. Corresponding author: e-mail: jiming@cumt.edu.cn

It is expected that we can know the characteristics of underground dynamic disasters by means of monitoring and predicting methods. Although there are many practicable methods, such as regression fitting [5-6], grey prediction [7-9], support vector machine [10], and so on, but they have poor ability of nonlinear mapping, and lack the ability of self-learning, self-organization, association, high fault tolerance and anti-interference to solve complex nonlinear problems[11]. Delightfully, Artificial Neural Network has overcome those above mentioned shortcomings and have been widely used to predict and evaluate in underground engineering in recent years [12], such as the pressure of roadway roof and working face [13-15], the surrounding rock deformation of roadway and tunnel [16-19], the damage depth of roadway floor [20] and the risk of gas emission [21] and rock burst [11, 22-23], etc.

2. BP neural network model

The BP neural network (error back propagation neural network) is a kind of multilayer feed forward network consisting of nonlinear transformation units. Generally, it includes input layer, output layer and hidden layer [24-26], and its topological structure is shown in Fig.1.

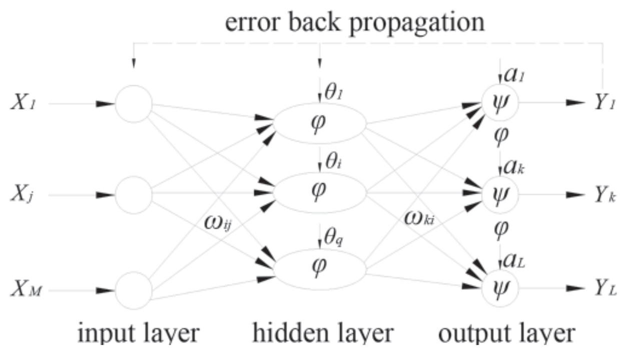


Fig.1 BP neural network

In Fig. 1, $X = \{X_1, \cdots, X_j, \cdots, X_M\}$ is the input layer of network, and are respectively the node thresholds of the hidden layer and the output layer of network, and are separately excitation functions of the hidden layer and the output layer of network, $\{Y = Y_1, \ldots Y_k, \ldots Y_L\}$ is the output layer of network, ω_{ij} and ω_{ki} are network weights.

(1) Input forward propagation

When the input layer is given X_j, the input of the i^{th} node of the hidden layer should be

$$net_i = \sum_{j=1}^{M} \omega_{ij} X_j + \theta_i \quad \ldots (1)$$

The output of the i^{th} node of the hidden layer is

$$y_i = \varphi(net_i) = \varphi(\sum_{j=1}^{M} \omega_{ij} X_j + \theta_i) \quad \ldots (2)$$

The input of the k^{th} node of the output layer is

$$\begin{aligned} net_k &= \sum_{i=1}^{q} \omega_{ki} y_i + a_k \\ &= \sum_{i=1}^{q} \omega_{ki} \varphi(\sum_{j=1}^{M} \omega_{ij} X_j + \theta_i) + a_k \end{aligned} \quad \ldots (3)$$

The output of the k^{th} node of the output layer is

$$\begin{aligned} Y_k &= \psi(net_k) = \psi(\sum_{i=1}^{q} \omega_{ki} y_i + a_k) \\ &= \psi[\sum_{i=1}^{q} \omega_{ki} \varphi(\sum_{j=1}^{M} \omega_{ij} X_j + \theta_i) + a_k] \end{aligned} \quad \ldots (4)$$

(2) Error back propagation

In order to make the final output of network approximate expectations as far as possible, two steps need to be carried out. Firstly, starting from output layer, the neurotic output error of each layer is calculated layer by layer. Secondly, the weights and thresholds of each layer are corrected according to the error gradient descent method.

For each sample p, its quadratic error criterion function is

$$E_p = \frac{1}{2} \sum_{k=1}^{L} (T_k - Y_k)^2 \quad \ldots (5)$$

For ρ training samples, the total error criterion function is

$$E = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - Y_k^p)^2 \quad \ldots (6)$$

The correction formula of error gradient descent method is

$$\left.\begin{aligned} \Delta\omega_{ki} &= \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - Y_k^p) \psi'(net_k) y_i \\ \Delta a_k &= \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - Y_k^p) \psi'(net_k) \\ \Delta\omega_{ij} &= \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - Y_k^p) \psi'(net_k) \omega_{ki} \varphi'(net_i) X_j \\ \Delta\theta_i &= \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - Y_k^p) \psi'(net_k) \omega_{ki} \varphi'(net_i) \end{aligned}\right\} \ldots \quad (7)$$

In the formula, $\Delta\omega_{ki}$ is weight correction value of the output layer; $\Delta\alpha_k$ is threshold correction value of the output layer; $\Delta\omega_{ij}$ is weight correction value of the hidden layer; $\Delta\theta_i$ is threshold correction value of the hidden layer.

When the output error meets the requirement of accuracy given, the network training has been finished.

BP neural network training steps are shown in Fig.2.

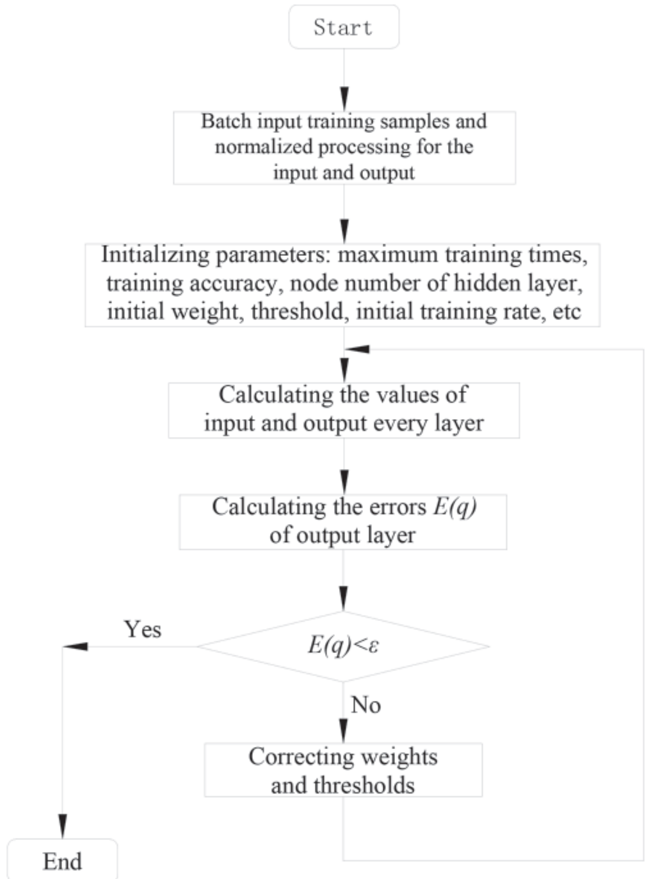


Fig.2 Training process of the BP neural network

3. Analysis of project case

3.1 Pressure monitoring in the working face

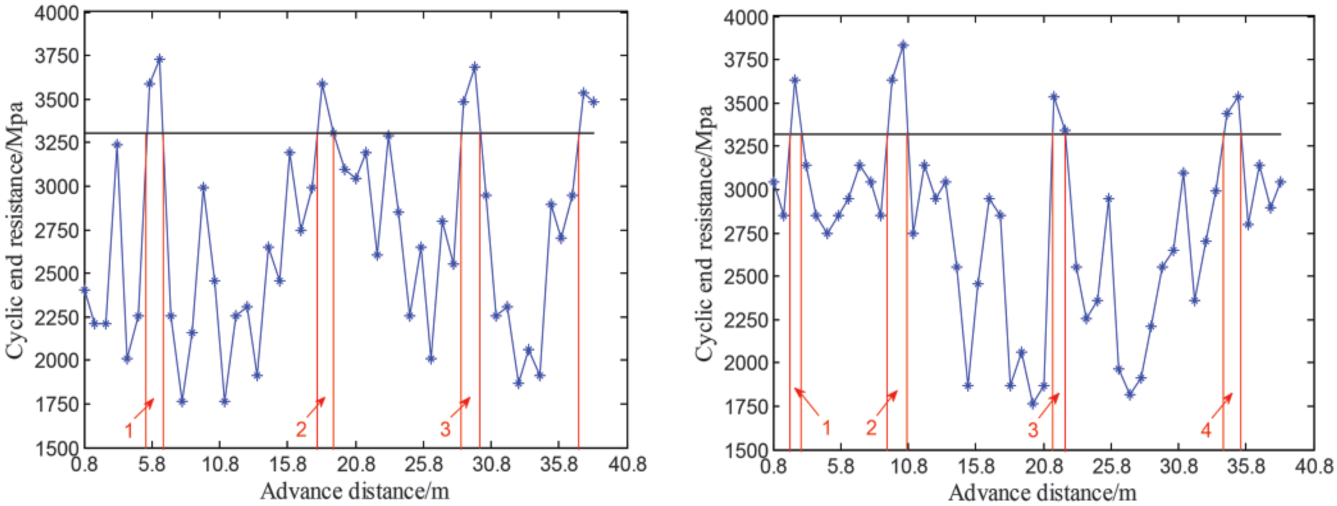
For the sake of knowing the law of roof pressure in the 02178 working face of the Huopu mine, the working resistance of hydraulic support is monitored [27].

(1) Monitoring equipment

In the monitoring process, six YHY60 mine intrinsically safe type digital pressure gauge, one FCH32/0.2 mine data collector and one communication adapter is used, as well as three power supplies is equipped.

(2) Layout of equipment

The YHY60 mine intrinsically safe type digital pressure gauge is installed on the hydraulic support of the working face, and data is monitored and collected through the FCH32/0.2 mine data collector. The length of 02178 working face is



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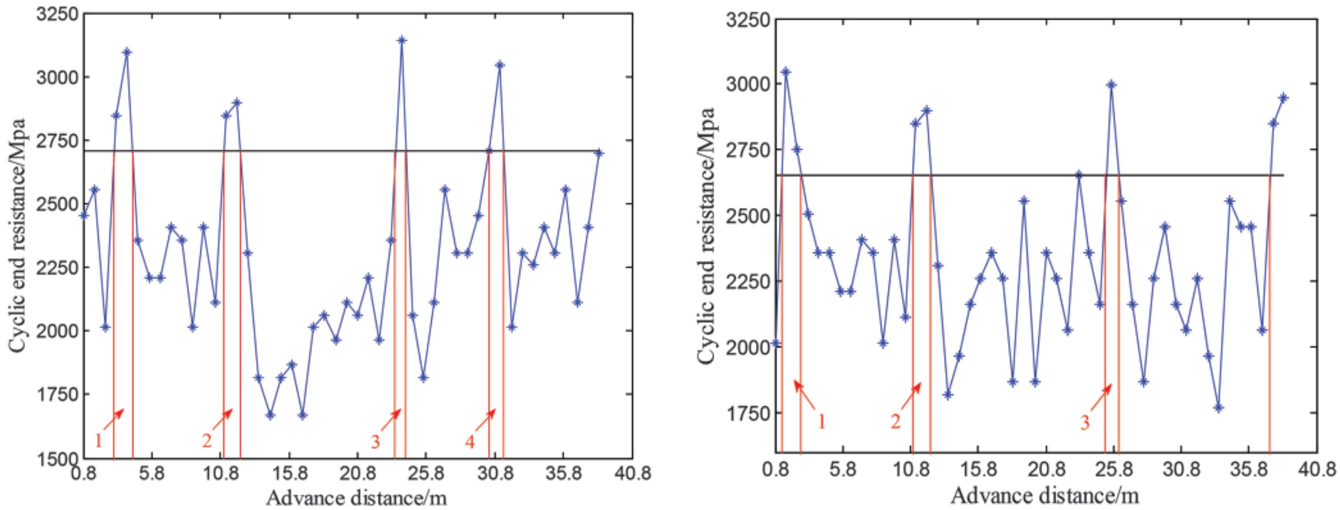

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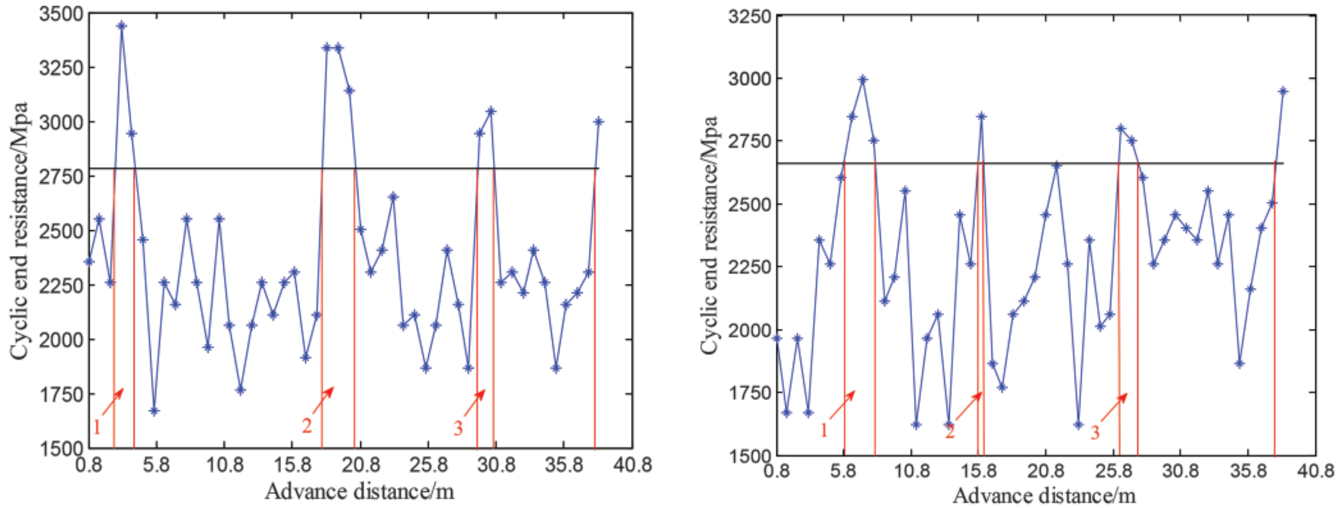

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Fig.3 Monitoring curve of cyclic end resistance of hydraulic support in the working face

Table 1 Statistical periodic weighting length and strength in the working face

position	Serial number	Weighting step/m	Influence range/m	Weighting average resistance/kN	Weighting maximum resistance/kN	Non-weighting average resistance/kN	Average dynamic coefficient
Under part	7#	10.40	1.33	3559.43	3600.34	2503.79	1.44
	20#	10.67	1.33	3551.25	3633.07	2623.47	1.38
	average	10.53	1.33	3555.34	3616.71	2563.63	1.41
Middle part	33#	9.33	1.33	2970.28	3027.56	2191.12	1.38
	46#	11.73	1.60	2937.55	2978.47	2237.42	1.33
	average	10.53	1.47	2953.92	3003.02	2214.27	1.36
Upper part	59#	11.47	1.60	3087.57	3125.75	2199.55	1.42
	72#	10.40	1.60	2817.54	2863.91	2212.03	1.29
	average	10.93	1.60	2952.56	2994.83	2205.79	1.36
Total average		10.67	1.47	3153.94	3204.85	2327.90	1.38

118.5m and a total of 79 hydraulic supports was installed. Starting from the 7^{th} hydraulic support of under part of working face, aYHY60 mine intrinsically safe type digital pressure gauge is arranged every passing 13 supports. Namely, the pressure gauges are respectively installed on the 7#, 20#, 33#, 46#, 59# and 72# hydraulic support and the layout of pressure gauge is shown in Fig.6.

0.8m-advance distance would collect a set of data, and the working face continuously advanced 38.4m. That is to say, 48 sets of data are obtained. The pressure criteria of hydraulic support is respectively 3318.11kN, 2706.48kN, 3301.44kN, 2655.78kN, 2783.3kN and 2661.22kN and the curves of monitored data are shown in Fig.3.

Through analyzing Fig.3, in the period of periodic weighting of 02178 working face, the average periodic weighting step is 10.67m, and the influence range is 1.47m; the average working resistance of hydraulic support is 3153.94kN, taking up 83% of rated working resistance (3800kN), and the maximum working resistance is 3204.85kN, taking up 84.34% of rated working resistance (3800kN). In the period of non-periodic weighting, the average working resistance is 2327.90kN. And the average weighting dynamic load coefficient is 1.38. The specifics are shown in Table 1.

During the weighting of working face, the roof pressure is severe. Two roadways appeared some phenomenon, such as coal wall caving, hydraulic monomer being crushed to death and roof evidently sinking. The roof of working face fell gangue seriously, and some hydraulic supports have difficulties to move. These seriously impacted on the recovery efficiency and progress, and brought safety risks for the high efficiency production of coal mine.

3.2 Modeling and pressure prediction

(1) Modelling

The research shows that there is a close relationship between the weighting and advance distance of working face, and it has evident periodicity, which is also called periodic weighting step. According to the cyclic end resistance of hydraulic support in the 02178 working face, BP neural network model is built. In the model, the field monitored data is regarded as input layer, and the hidden layer used sigmoid transfer function, and the output layer output the cyclic end resistance of hydraulic support of advance distance being more than 38.4m.

A time series X = $\{X(1), X(2), ...X(n)\}$ ($n = M$) are consisted of the monitored data. In the time series, the cyclic end resistance of hydraulic support when the working face advances 0.8m, similarly, the cyclic end resistance of hydraulic support is the advance distance of working face of 38.4m [28-29]. Suppose time series step equals 4, then the 5th resistance value could be predicted by the former four continuous monitored data. So the input and output of BP neural network prediction model of working face periodic (weighting Table 2).

Set the network training speed be 0.05, the maximum training times be 100000, and the average error be less than 0.5×10^{-5}. By training network, the prediction errors from different hidden layer nodes (6, 12, 18 and 24) are compared and the optimal nodes would be found [20, 22]. Taking 20# and 33# hydraulic supports for example, their cyclic end resistances are predicted in the 4th weighting process. The relative error between the output of network and the monitored data are shown in Fig.4 and Table 3.

Table 2 Method of input and output in the prediction model

Four input	One output
$x(1)$, $x(2)$, $x(3)$, $x(4)$,	$x(5)$
$x(2)$, $x(3)$, $x(4)$, $x(5)$,	$x(6)$
|	|
$x(n-4)$, $x(n-3)$, $x(n-2)$, $x(n-1)$,	$x(n)$

Table 3: Relative errors of different hidden layers

Node of hidden layer hydraulic support	Relative error/%			
	6	12	18	24
20#	0.0824	0.0638	0.0775	0.1035
33#	0.0965	0.0665	0.0734	0.0877

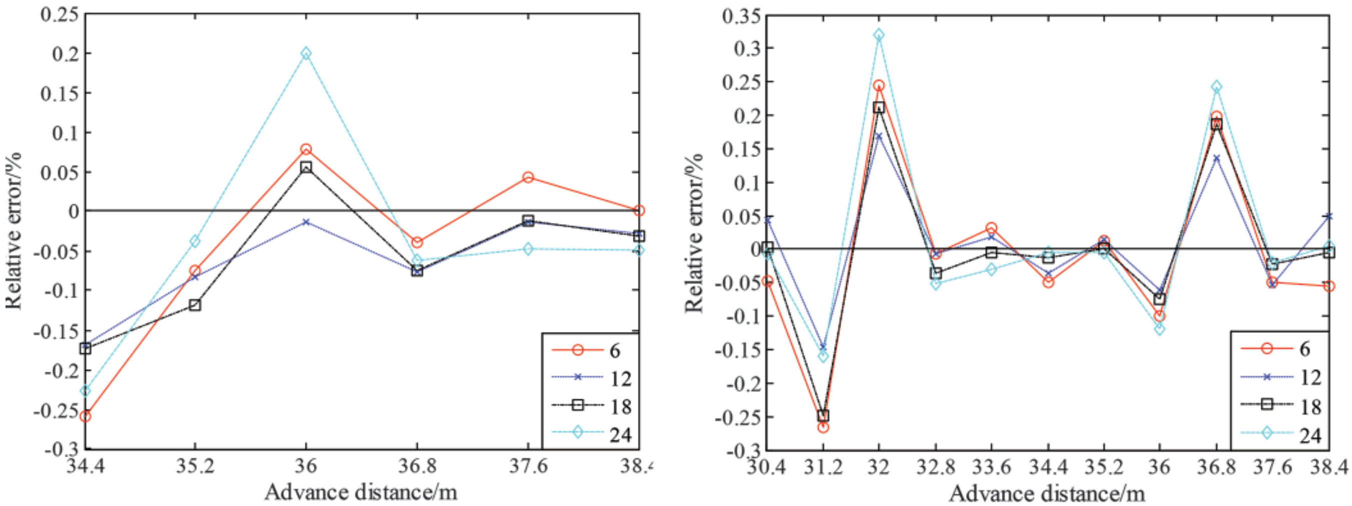

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Fig.4 Curve of prediction error

TABLE 4 PREDICTION OF CYCLIC END RESISTANCE OF HYDRAULIC SUPPORT IN THE WORKING FACE

Hydraulic support	7#	20#	33#	46#	59#	72#
Advance distance	3301.44	3318.11	2706.48	2655.78	2783.3	2661.22
39.2	3142.16	2945.85	2651.43	3029.20	2748.04	2748.43
40	3238.48	2701.15	2260.72	1879.06	2025.51	2794.81
40.8	3043.54	3315.00	1920.38	1966.01	2652.00	2406.55
41.6	2945.35	3191.34	2498.95	1595.78	2780.77	2013.81
42.4	3237.84	2945.90	2018.57	2256.44	2453.17	1963.67
43.2	2752.01	2408.16	2499.94	1873.25	2209.89	2546.80
44	3434.77	2207.82	2601.36	2450.85	2305.56	1868.68
44.8	3625.62	2257.30	2845.98	1874.86	2066.48	2061.89
45.6	3046.01	3423.28	3104.12	2648.71	2782.42	2837.90
46.4	2313.54	3627.76	2651.66	2937.11	3033.88	2747.29
47.2	2697.41	3534.87	2454.26	2066.72	2405.47	2406.25
48	3138.87	2799.71	2799.01	2161.18	2114.74	2308.40

From Table 3, it could be told that the error between BP neural network model and the actual data are very small. To some extent, both can perfectly coincide.Therefore, the predicted value is able to react the weighting of working face with the same geological conditions. The comparison indicated that the relative error is the smallest when the hidden layer has 12 nodes and the relative errors of two supports are 0.0638% and 0.0665% respectively. So, the BP neural network structure chose 4-12-1. Clearly, the network model contained 4 nodes in the input layer, 12 nodes in the hidden layer and 1 node in the output layer. Then the 4-12-1 network is trained by monitored data. Finally, by using the mature BP neural network trained, the periodic weighting of working face is predicted.

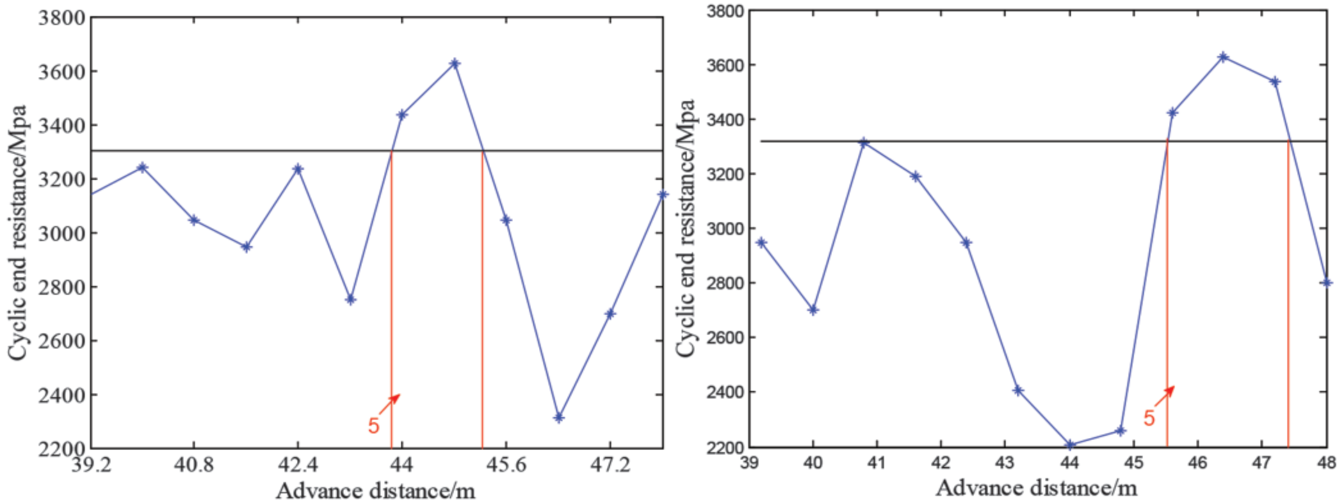
(2) Prediction and analysis of the periodic weighting of working face

After field monitoring, the force of hydraulic support, which was used to analyze the weighting characteristics of working face, is predicted. Here, the advance distance of 39.2~48m is taken into consideration. Consequently, the curve of predicted cyclic end resistance of hydraulic support is shown in Fig.5, the details are shown in Table 4.

According to the prediction results, the 5th weighting characteristics of working face are found and given in Table 5.

In summary, for the whole working face, the average weighting step is 9.1m, and the average influence range is 1.53m, and the average dynamic load coefficient is 1.28. The periodic weighting of working face period is displayed in detail in Fig.6.

To reduce the impact of periodic weighting on the normal production, referring to Table 4 (roof pressure) and Fig.6 (weighting range), some measures, including advanced support in the roadway roof weighting areas and moving supports with pressure in the working face, are carried out. Compared without measures, the conditions of roadway



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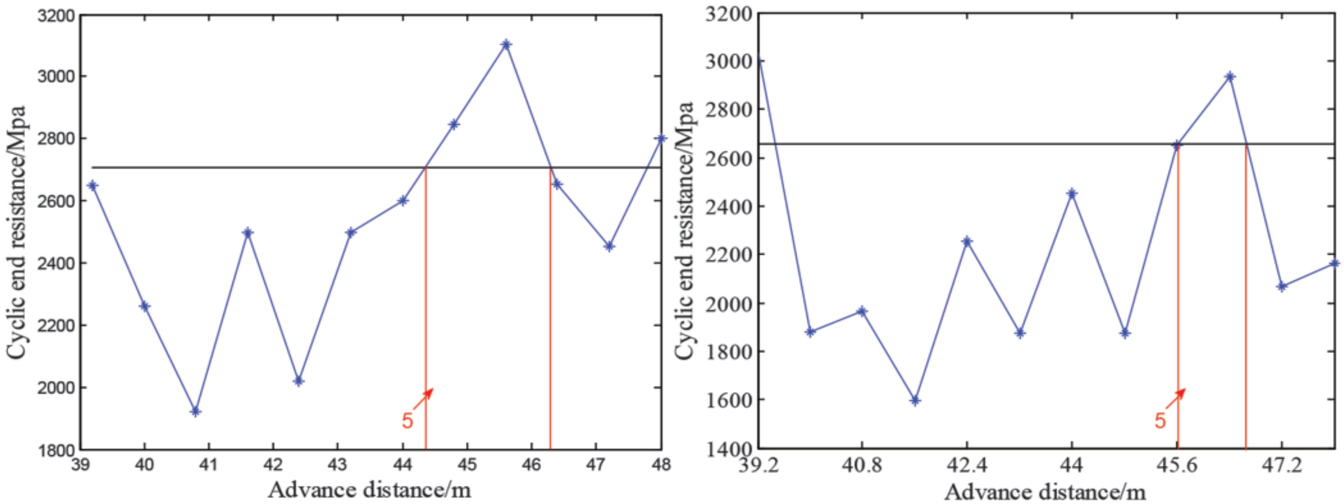

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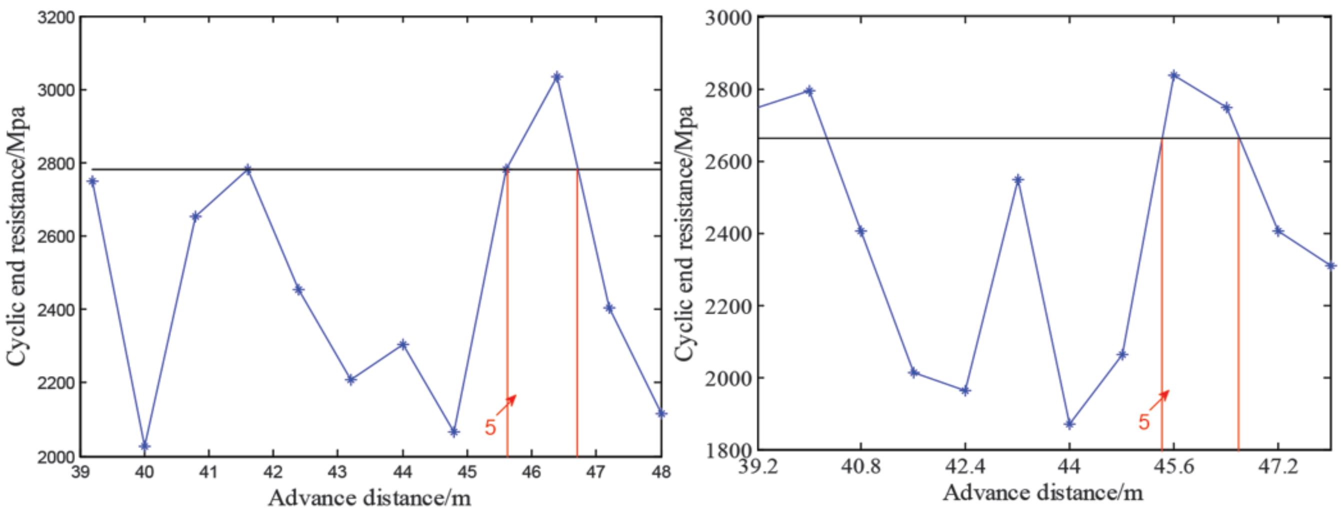

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Fig.5 Prediction curve of cyclic end resistance of hydraulic support in the working face

Table 5 The 5th weighting characteristics of working face

Position	Serial number	Weighting step/m	Influence range/m	Average dynamic coefficient
under part	7#	6.40	1.50	1.23
	20#	11.20	2.00	1.32
	average	8.80	1.75	1.28
middle part	33#	14.40	1.90	1.27
	46#	8.00	1.10	1.36
	average	11.2	1.50	1.32
upper part	59#	7.20	1.20	1.26
	72#	7.20	1.50	1.23
	average	7.20	1.35	1.25

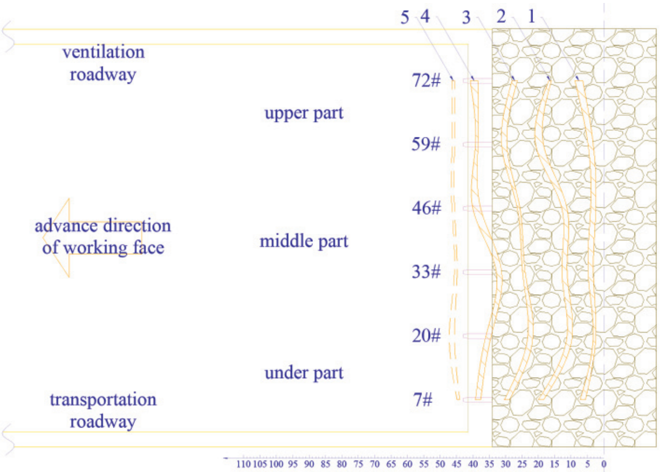

Fig.6 Distribution of periodic weightingin the working face

surrounding rock and working are markedly improved, which would provide safety guarantee for underground production. Meanwhile, the on-line monitored data of the cyclic end resistance of hydraulic support shows that the roof pressures significantly increased in these are as, and it indicates that the prediction results of BP neural network model are accurate and reliable. Therefore, it is extremely necessary to predict real-time weighting areas and its influence range and take relevant measures.

4. Conclusions

As the 02178 working face of Huopu mine advances, the cyclic end resistance of hydraulic support is monitored, and the periodic weighting characteristics of working face are understood. The average weighting step, influence range and dynamic load coefficient are respectively 10.67m, 1.47m and 1.38. Based on BP neural network theory and error analysis, a periodic weighting prediction model, whose network structure is 4-12-1, was built. By the model, the 5th weighting prediction results are as follows: the average weighting step is 9.1m, and the average influence range is 1.53m, and the average dynamic load coefficient is 1.28. The output value of model is basically consistent with the field monitored data. And it can successfully describe the weighting state of working face with the same conditions, which provides the theoretical basis for the roof control. Therefore, this method is reasonable and feasible, and the prediction results are of practical guiding significance for the safe and efficient production of underground mining.

Conflict of interests

The authors declare that there is no conflict regarding the publication of this paper.

Acknowledgements

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