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Research Article

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Application of BP neural network in predicting the cement materials performance

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ABSTRACT

The 4-10-5 prediction network model was established based on the improved BP neural network, considering that the performance of cement materialsare impactedby many factors and the multivariate cross of those factors are difficult and strenuous to study in laboratory. Furthermore, the network model was trained and tested with the data collected from the laboratory test results. The results showed thatthe prediction precision of the well trained network model is high and reliable, whose fitting correlation coefficient and average prediction error are 0.969 and 6.72% respectively. Finally, the well trained network model was applied to predict the optimal material ratio, which can meet the requirement. Specifically, the optimal material ratio of fly ash, quicklime, cement, and gangue in cement materials are 35%, 10%, 2%, and 53% respectively, and the concentration of slurry is 77% by the above proportion.The cemented backfilling materials under this ratio has good effect in field application which prove the reliable of this prediction model.

Keywords:cemented backfilling materials; material ratio; performance prediction; BP neural network;Matlab toolbox

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With the development of mining technology, "Green Mining" has become the future trend.The backfilling mining technologyis an important way to achieve the"Green Mining"[1~3].Among the numerous backfilling mining technologies, the cemented backfilling mining technology is an effective method,which is based on the gangue and fly ash as the main fillingmaterials.In this method, the backfilling slurry is made from a certain proportion of gangue, fly ash andcementing materials. Theslurry is made with no need for dewatering process and then piped to the undergroundby using the filling pump to fill the gob timely [4].Cement materials is the core of cemented backfilling mining technology and their properties, such as slump, bleeding rate, different age strength, etc.are the key to the successful applications of the technology. The performance of Cement materialsare impactedby many factors [6-7] includingnot only established and quantifiable factors, but also some uncertain or obscure factors, which is of complex non-linear relationship between them[8].In order to study the performance of cemented filling materialsunder different influence factors, manyscholars have mainly conducted the tests in laboratory.However, most research to date only focus on single-factor[9-11]and unable tohave comprehensive analysis of multivariate cross which need a large amount of labor and have puzzledengineerson mining production decisions infield applications [12].

BP neural network(BPNN) is one of the most widely used neural network model which is one kind of multilayer feed forward network trained by error back-propagation algorithm [13].The network model can achieve nonlinear mapping between the input samples and the output samples, and it have features of self-organizing and self-learning that make it effective at nonlinear approximation. Moreover, the underlying relationship betweenthose data can be induced through learning process of its own accord[14~15]. Therefore, the BPNN isapparently effective in predicting the performance of cemented filling materials, such as Zhou Huaqiang, ChangQingliang, Wei Wei and other scholars have done those relatedresearch, but only built a network modelwith one single output for one performance of the materials[7~8].In order to solve the problem ofpoorspeed of converging and easy to fall into local minimumin the application of standard BPNN model,the additional momentum and self-adaptive learning rate are introduced to improved BP network standard algorithm[8]. The improved network is of stronger mapping capabilities, higher network training speed and avoiding falling into local minimum.

In this paper, the performance of cement materialsis abtainedby laboratory test on different materials ratio.Based on the improved BPNN,the prediction model with multi-inputand multi-output is established to predict the performance of cemented filling materials, whose structure is 4-10-5.Specifically, the slump, bleeding rate, 3d、7d and 28d age strengthcan be predicted under different concentration ,fly ash ,quicklime and cement consumption. And the model was trained and tested by laboratory data with Matlab7.1 platformand then it was applied in Gonggeyingzi coal mine.The results shows that the precision of prediction is high and reliable and meets the needs of production practice.

1 Improved BPNN model[13]

1.1 Additional momentum method

Based on back-propagation method, a value which is proportional to the previous weight variation is added to each current weight variation, then a new weight variation is obtained. The weight adjustment formula with additional momentum factor are as follows.

$$\begin{aligned}\Delta w_{ij}(k+1) &= (1-mc)\eta\delta_i p_j + mc\Delta w_{ij}(k)\\ \Delta b_i(k+1) &= (1-mc)\eta\delta_i + mc\Delta b_i(k)\end{aligned} \quad (1)$$

Where

*k*is the number of training;

*mc*is the momentum factor which is about 0.95 generally;

$\Delta w_{ij}(k+1)$ and $\Delta w_{ij}(k)$ arethe revised and the current weight difference respectively;

$\Delta b_i(k+1)$ and $\Delta b_i(k)$ arethe revised and the current threshold difference respectively;

η islearning rate;

$\delta_i p_j$ and δ_i arethe current weight and the thresholdsgradient respectively.

1.2Self-adaptive learning rate

Self-adaptive learning rate can ensure that the network is always training at the maximum acceptable learning rate. The learning rate will reduce when a new error exceeds a certain multiple of the old one, otherwise the learning rate remain stable. On the other hand, the rate will increase when a new error is smaller than the old one. An adjustment method of adaptive learning rate is shown in formula (2).

$$\eta(k+1) = \begin{cases} 1.05\eta(k), SSE(k+1) < SSE(k) \\ 0.7\eta(k), SSE(k+1) > 1.04\cdot SSE(k) \\ \eta(k) \end{cases} \quad (2)$$

Where

$\eta(k+1)$ and $\eta(k)$ arethe revised and the current learning rate respectively;

$SSE(k+1)$ and $SSE(k)$ arethe revised and the current variance respectively.

2Cement materials laboratory testing

2.1Composition of cement materials

According to the actual situation of coal production, cement materialsare consisted ofgangue, fly ash, quicklime, cement and water which mixed together in a reasonable proportion in whichgangue acted as coarse aggregate,fly ash acted as fine aggregate, quicklime and a small amount of cement acted as binder.

The particle size of gangueare required no more than 25mm in order to achieve pumping and a long-distance pipelines transport ofcement materials.The fly ash, whose diameter is0.005~0.05mm,is mainly used to fill the gaps between the coarse aggregate, in which the ultrafine grain size hasa larger surface area and sufficientsaturated aqueous.After combination with water molecules they distribute in the gaps between the aggregate, which ensure the workability and the stability of the solid particles on structure surface of the cemented filling materials. Thecalcium oxide takes 39% in quicklime, whose role is to stimulate the activity of quicklime to generatethe hydraulic cementations material. The cement works as lubricantin the process of filling materialstransportationand alsoincrease the adhesion of the slurry during the solidification process, which ensure the filling body has a higher carrying capacity.

In order to test the components ofmaterial mineral in cemented backfilling materials, XRD method is used and the results of X-ray diffraction shown in Figure 1.

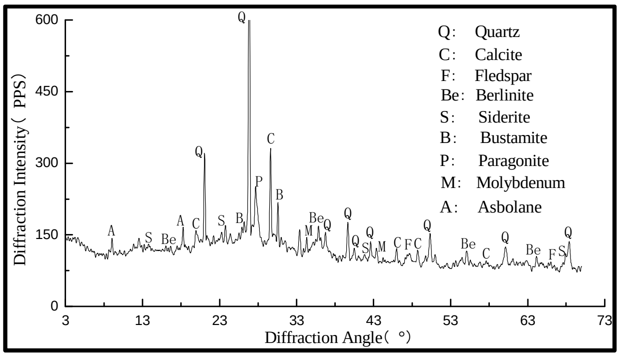


Fig1 X-ray diffraction pattern of cemented backfilling materials

Figure 1 shows that the main mineral composition of the cement materials are quartz, calcite, feldspar,berlinite and siderite, and it also contains small amounts of bustamite, paragonite, molybdenum and asbolite. The more content of quartz in materials leads to a higher bearing strength, and the calcite, feldsparmica, siderite and other materials are easy to bring hydrolysis and weathering phenomena to the materials.

2.2 Test ratio

The ratio of each component in cement materialshas a great influence on the performance of cement materials for they are made of a variety of materials. Therefore,the concentration of slurry, the proportion of fly ash, quicklime and cementare adjusted reasonably to test their corresponding performance. The specific ratio of test program are shown in Table 1.

Tab.1Ratio of cement materials test

No. of ratio	Concentration of slurry /%	Dry percentage /%			
		Fly ash	Quicklime	Cement	Original gangue
1	73	40	10	2.5	47.5
2	74	40	10	2.5	47.5
3	75	40	10	2.5	47.5
4	76	40	10	2.5	47.5
5	77	40	10	2.5	47.5
6	75	30	10	2.5	57.5
7	75	35	10	2.5	52.5
8	75	45	10	2.5	42.5
9	75	50	10	2.5	37.5
10	75	40	6	2.5	51.5
11	75	40	8	2.5	49.5
12	75	40	12	2.5	45.5
13	75	40	14	2.5	43.5
14	75	40	10	0	50
15	75	40	10	1.5	48.5
16	75	40	10	3.5	46.5
17	75	40	10	5	45
18	74	35	10	2.5	52.5
19	76	40	10	0	50
20	77	40	12	2.5	54.5

2.3 Testing program

The test was concentrated on the transportation performance and the compressive strength of different ratio of cement materials.

(1)Test on the transportation performance of slurry

The test on the transportation of slurry arecomposed of the slump test and the bleeding rate test.Slump is a simpleand intuitive reference index in engineering operations when pumpcement materials, and its valuedirectlyreflect the flow state and the frictional resistance of cement materials. Bleeding is the phenomenon which coarse aggregates goes down and water floats up during the transportation, vibration and pumping process of cement materials.And the phenomenon of segregation will be produced in the transportation process when the bleeding rate of slurry is too large, which lead to a pipe blockage. Both these tests refer to the *standards method in* o*rdinary concrete mixture performance test* (GB/T 50080-2002).

(2) Test onthe compressive strength of cement materials

The70.7mm×70.7mm×70.7mm standard test cube is used as specimen. The specimen is moved to maintain under a standard conditions with the temperature 20±2℃and the relative humidity 95% after kept in the mould for 1d, Then kept in the mould for 3d, 7d and 28d in the same way to test their compressive strength.

In order to conduct the uniaxial compression test, SANS mechanics of materials testing machinewas used with a load speed of 1mm/min. The uniaxial anti-compressive strength value was obtained by calculating the average value of 3 specimens taken from each group.

2.4 Testing result

The performance index of cement materials with different ratio were shown in Table 2 based on the above test.

Tab.2 testing result

No. of ratio	Slump /mm	Bleeding rate /%	Compressive strength/MPa		
			3d	7d	28d
1	245	3.95	0.52	0.77	1.27
2	240	3.84	0.61	0.86	1.65
3	230	3.44	0.71	1.22	1.83
4	165	2.95	0.85	2.13	2.91
5	150	2.09	0.96	2.65	3.2
6	237	3.9	0.67	1.39	1.58
7	200	3.8	0.71	1.56	1.65
8	152	1.73	0.95	1.92	2.49
9	143	1.66	0.83	1.67	2.04
10	226	3.68	0.53	1.08	1.55
11	205	3.55	0.73	1.25	1.77
12	168	1.88	0.82	1.69	2.92
13	154	1.75	0.65	1.46	2.72
14	205	2.67	0.58	0.74	0.8
15	217	2.64	0.66	1.16	1.64
16	220	2.65	0.85	1.28	1.73
17	200	2.67	0.96	1.35	1.91
18	247	3.86	0.65	0.98	1.46
19	165	2.41	0.62	1.39	1.74
20	150	1.84	1.05	2.27	3.33

3 Cement materials performance prediction model

3.1 Establishment of prediction model

It has been proved theoretically that the feed forward network with 3-layer can approximate any continuous function in any arbitrary precision and the feed forward network with deviation, at least one S hidden layer and one linear output layer can approximate any rational function [13].Therefore,the network was determinedto three layers, namely oneinput layer, oneoutputlayer and onehidden layer.Based on the laboratorytest,the input layer have 4 nodes which corresponding to the four variables of the cement materials, namely the concentration, fly ash, quicklime and cement, while the output layer has 5 nodes, which correspondingto slump, bleeding rate, compressive strength in age of 1d, 3d and 28d.

There is no explicit method to determine the number of nodes in the hidden layer so far,Such as Homik indicated the number of nodes in the hidden layer may between $\sqrt{2m+1}$ and $2m+n$, Hecht Nielsen pointed out that the number is $2m+1$[8], and another scholar raised the number is $\sqrt{m+n}+a$, in which *a*is a constant between 1 and10 [16].Inthese methods, m and n are the number of nodes in the input layer and the output layer respectively. Therefore, the number of node in the hidden layer can be calculated as 3~13 based on the above empirical formulas.

Taking the complex relationship between material performance and influence factors into account, the function *tansig* and *purelin*are selected as the transfer functions for hidden layer and output layer respectively.

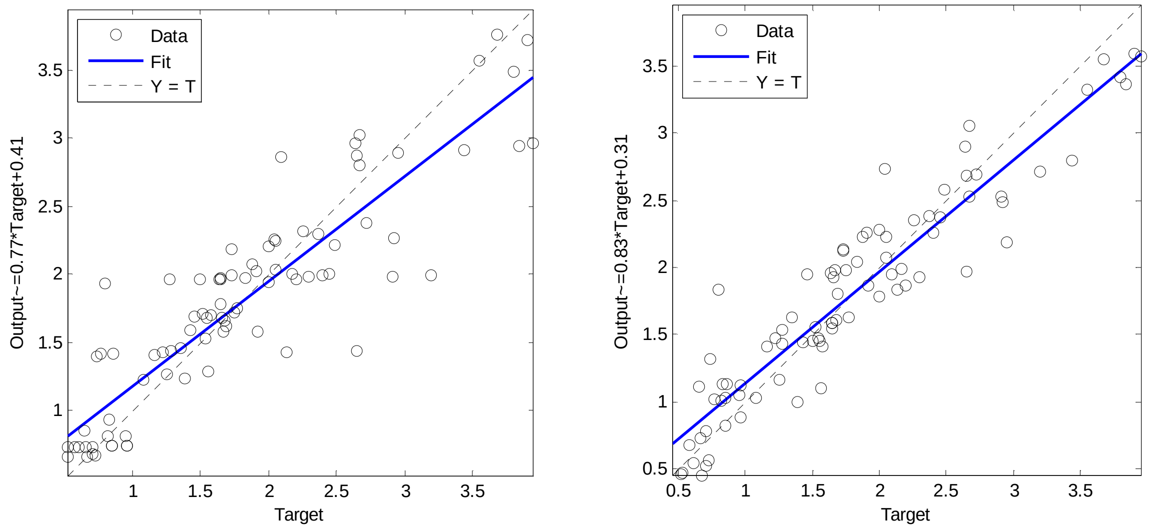
3.2 Training and prediction

The data of the first 17 groups fromTables 1 and Table 2areselected as training samples, while the rest acted as test samples. *Traingda*self-adaptive learning algorithm is used to complete the network training and prediction, which was programed and operated under Matlab7.1 environment. The main parameters of the network are as follows: the target error is 0.0001, the maximum calculated numbers is20,000,and theadditional momentum factor is 0.90.

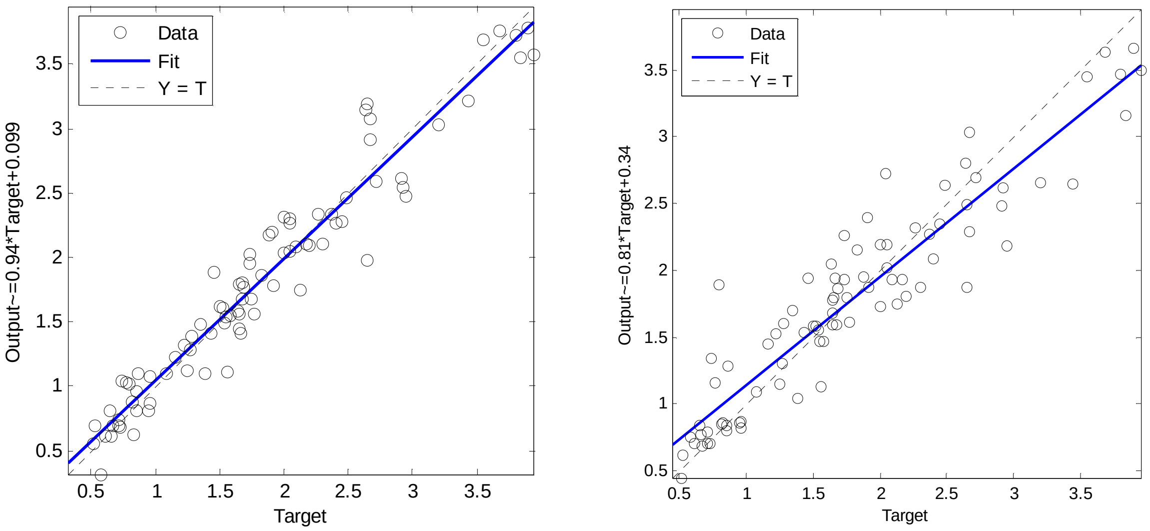
The typical training results are shown in Figure 2 for the training network with different numbers of nodes in the hidden layer,andthe training error of network performance (MSE) and the fittingcorrelation coefficient of training results (R) are shown in Table 3.

Tab.3 The performance of different numbers of nodes in the hidden layer

Numbers of nodes in hidden layer	7	8	9	10	11	12	13
MSE	0.157	0.109	0.0871	0.0473	0.0834	0.0826	0.062
R	0.895	0.928	0.939	0.969	0.933	0.945	0.953



(a)Numbers of nodes in hidden layer is 7(R=0.895) (b)Numbers of nodes in hidden layer is 9(R=0.939)



(c)Numbers of nodes in hidden layer is 10(R=0.969) (d)Numbers of nodes in hidden layer is 11(R=0.933)

Fig.2Typical network training results

As shown in Table 3, the hidden layer with 10 nodes has the best performance in training, and it'straining result and error curve are shown in Figure 2 (c) and Figure 3 respectively.

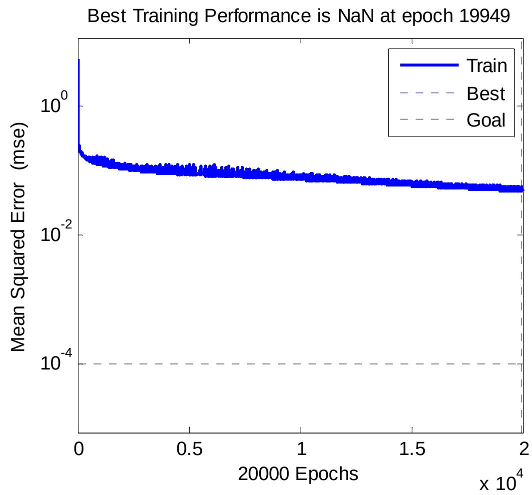


Fig.3 Curves of 10nodes of hidden layer network training errors

As shown in Figure 3, there is still exist difference between the training errors and the target errors due to more nodes in the output layer and less data sample, and also the cemented filling material is a multiphase composite media, whichexists uncertain factorsduring the performance test process.

The test sample was predicted using the trained network model with 10 nodes in the hidden layer and it's results are shown in Table 4.

Tab.4Test sample predictions

No. of ratio		18	19	20
Slump/mm	Measured value	247	165	150
	Predicted value	233	173	156
	error/%	5.67	4.85	4.00
Bleeding rate/%	Measured value	3.86	2.41	1.84
	Predicted value	3.74	2.20	1.92
	error/%	3.11	8.71	4.35
compressive strength of 3d /MPa	Measured value	0.65	0.62	1.05
	Predicted value	0.68	0.57	1.05
	error/%	4.62	8.06	0
compressive strength of 7d /MPa	Measured value	0.98	1.39	2.27
	Predicted value	1.09	1.50	2.00
	error/%	11.22	7.91	11.89
compressive strength of 28d /MPa	Measured value	1.46	1.74	3.33
	Predicted value	1.52	1.86	3.04
	error/%	4.11	6.90	8.71

As shown in Table 4, the error ofpredicting the performance of cement filling material by using the network model ranges between 0 to 11.89%, while the average error of 6.27%. Those results indicates that the performance prediction model of cemented filling material, based on the improved BPNN, has high prediction precision and generalization ability, which can be used to guide the production practice.

4 Engineering Applications

The cement backfilling mining technology is taken into application to mine the extremely thick seam under the aquifer in Gonggeyingzi coal mine which located in Chifeng, Inner Mongolia.Thecompressive strength of cemented filling material in 3d age requiresnot less than 0.6MPa due to this special mining technologyand in order to control the damage of roof strata after mining, the strength in 28d age requires not less than 2.0MPa.Moreover, in order to ensure the pumpability of the slurry, the slump is not less than 150mm and the bleeding rate is not more than 3%.

The performance of cemented filling material with different proportions are predicted by using the above trained network model in this paper Finally, the optimal proportion, which not only meet the performance requirements but also reduce the dosage of cement,is obtained as follows, fly ash:35% , quicklime:10% , cement :2% , and gangue :53%.The concentration of slurry is 77%. Moreover, the strength of the samples which got from field in 3, 7 and 28 age is 0.76Mpa, 1.62Mpa and 2.23Mpa respectively, and the slump is 176mmand the bleeding rate is 2.75%, which meets the requirements of engineering.It shows the prediction model is accurate and reliable. The field application is shown in figure 4.

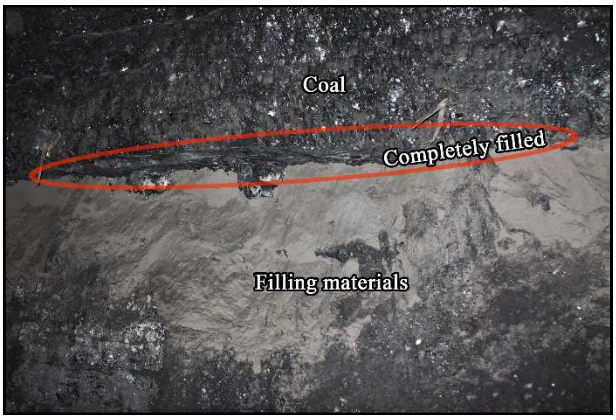


Fig.4The field application

CONCLUSION

(1) The performance prediction model of thecemented filling material with 3 layers in which the hidden layer has 10 nodes was established based on improved BPNNin this paper. Through this model the complex mapping relationshipbetween the performance of cemented filling materials such as the slump, the bleeding rate, the compressive strength in different ages and the ratio of the materials such as the concentration, the dosage of fly ash, quicklime, and cement is obtained to predict the performance of different ratio materials.
(2) The self-adaptive learning ratearithmetic is adopted to train the network with the training and testing sample data collected from the laboratory test results, and the training results of MSEand R are0.0473 and 0.969 respectively, which indicate a high precision.The prediction model was proved to meets the engineering requirements with the prediction error 0~11.89%，and the average 6.27%after testing the trained network model.
(3) The well trained network model was applied to optimize the ratio of the cemented filling materialin Gonggeyingzicool mine.Finally, the optimal proportionis obtained as follows, fly ash:35%，quicklime:10%，cement :2%，and gangue :53%. And the concentration of slurry is 77%.This ratio not only meets the requirements but also have low cost and good application effect.

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