Prediction Strategy of Coal and Gas Outburst Based on Artificial Neural Network

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***Abstract*—The article describes the research of coal and gas outburst prediction technology and the new problems they face in the modern mining. It also describes the superiority of neural network technology in dealing with complex geological conditions. It refers to the possibility and necessity of combination of the coal and gas outburst prediction and artificial neural networks, and other high-technology, There are examples show that they can be applied to predict the course of coal and gas outburst and gas content .Practice has proved the prediction model that coal and gas outburst forecasting techniques and artificial neural network have established not only considers the various factors and better handle various kinds of the non-linear relationships in geological conditions ,but also having a forecast of high precision and reliable conclusions and provides a new way about the further development of coal and gas outburst prediction technology.**

***Index Terms*—artificial neural network, coal and gas outburst prediction, gas content**

I. INTRODUCTION

A.. The Dangers of Coal and Gas Outburst

Gas outburst does not only affect mine production, but also posing a threat to the safety of workers. Therefore, it is more important to study the issue of coal and gas outburst prediction. Coal and gas outburst is a disaster occurred during mining and also is an important cause of the accident which restricts the development of Chinese coal industry and threatens the safety of operating personnel [8]. According to statistics, nearly 300 pairs coal mine of China owned key coal mines are in outburst, so far, the number of coal and gas outburst has reached more than 16000 times, with the increasing of mining depth and mining expansion, such kinds of incidents will be more serious. Therefore, as a basic element of the outburst prevention work, the research on the trends of coal and gas outburst forecast and risk prevention have an important practical significance on the safety about the production process and operators.

B. The Complexity of Coal and Gas Outburst

Coal and gas outburst is a complex dynamic process and has a complex non-linear relationship with its influencing factors [17]. As we all know, the main three elements of the coal and gas outburst are pressure (including the additional pressure caused by the mining face), gas, physical and mechanical properties of coal mine. The leading role induced the prominent factors depend on the specific conditions of each mine because of the coal mine mining and the difference of geological conditions. The current forecast establish on the basis of comprehensive hypothesis. The usual way: first, we make a subjective judge to all kinds of warnings to coal and gas outburst by means of the experience. The second way is based on the stress on the front of coal, as volume, gas pressure, physical properties and mechanical properties changes of coal. Then we measure the Indicators of the coal and gas outburst and determine the outburst after comparing with the corresponding critical value. This method in the prediction of coal and gas outburst plays a positive role but it also has some problems.

C. The Existing Methods of Coal-gas-outburst Prediction

At present, many domestic and foreign scholars in the course of its research and development explore and summarize a variety of forecasting methods, for example, Phenomenon observation method, R-value composite indicator method, shell instability method, Composite indicator D and K method, Coal cuttings and gas adsorptions indicator method, Initial rate of gas emission drilling method, Single indicator method and gray prediction method and gas geological method. But as is known to all, Outstanding is subject to the combined effect of three factors that are gas, stress and coal structure. It has some factors even that are not recognized by people. Thus, we accurately use the existing theory to express the interaction between the factors and determine the impact of their outstanding to be impossible.

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D. The New Method on Coal and Gas Outburst Prediction

At present, many domestic and foreign scholars are working on coal and gas outburst prediction. Artificial neural network is composed of large scale interconnected neurons and is a highly nonlinear dynamical systems based on the simulation of the human brain information processing mechanism [2]. It also is the abstraction and simulation certain basic features to the human brain and natural neural networks. It has the "learning" capability through the samples. This new method is different from the traditional variety of forecasting methods. In practical application, we do not need to make any assumptions between the factors and the correlation of outburst.

The artificial neural network has nonlinear approximation ability. It truly depicts the nonlinear relationship between input variables and output variables [3]. This non-linear relationship between input variables and output variables can just reflect relationship between affecting factors and outburst results.

II. THE BASIC PRINCIPLES OF BP NEURAL NETWORK THEORY

A Back Propagation Network Model

At present in the practical application of ANN, the vast majority of the network model is using BP networks (Back propagation ANN) and its variations. It reflects the most essential part of ANN. BP network is a multi-layer feed forward network of one-way transmission. BP network can be seen as a high non-linear mapping from the input to the output. It is integrated through a simple nonlinear function for several times. It can be approximated to the complex functions. Theoretical studies have shown that, it can achieve any desired accuracy in any continuous function in the BP network.

BP network is a neural network which is currently the most widely used in engineering applications [5]. It includes input layer, hidden layer and output layer. His most prominent feature is that and it can realize the highly non-linear mapping from R^n space (n is the input nodes) to the R^m space (m is the output layer nodes) under the help of sample data , and this mapping result can have enough training samples which come from experimental data or simulation data to ensure. Color figures will appear only in online publication. The Back propagation network model is shown in figure 1.

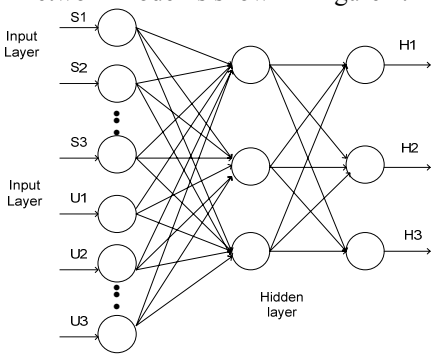

Figure1 Back propagation network model

BP network learning is a typical mentor learning, which is achieved by the BP algorithm. BP algorithm belongs to algorithm .It is a supervised learning algorithm which consists of two parts: the forward transmission of information and error back propagation. In the forward propagation process, the input information is transmitted to the output layer compute layer through the hidden layer. The state of neurons in each layer only affects the state of neurons in the next layer. If it does not get the desired output in the output layer and then calculate the error change value of the output layer. Next it turn back propagation, making the error signal through the network along the original connection back-propagation path to turn back and then modify the weights of neurons in each layer until it reach the desired goal.

Structurally, three-layer BP neural network is a typical feed back level network of semi-linear, which is divided into input layer, middle layer (or hidden layer, hidden layer) and the output layer. The nodes in the same layers are not associated, the nodes in the different layers can connect with the prior nodes. Among them, the input layer of BP network nodes correspond to the number of inputs which can be perceived [4]. The nodes of output layer corresponding to the output number of BP network output; The number of middle layer nodes are set according to need. The basic idea: first, it sends the input mode through the network, and then calculating the error between the actual output and the ideal output. It attributes the error to the "fault" of connection weights between each node in the link layer and the threshold. It shares to all connected nodes by the back-propagation of the output layer error to the node of input layer by layer. It can calculate the reference error of the connected node. Then it can make corresponding adjustments to the connection weights and make the network tend to the map of the requirements [1]. It constantly repeats the process of "input mode, error calculation, back-propagation, weight adjustment" process. The error between the actual network output and the ideal output continuously decreases until finally obtain the desired output; e-learning (or network training) will come to an end.

B Arithmetic of Back Propagation Network

BP algorithm is a back-propagation method (Back Propagation Algorithm) based on gradient descent [2].The main algorithm process is as follows: first, the given error ε is greater than 0, learn rate, η is greater than 0, the selected initial weights is W_k .Second, we calculate the network output, if the difference between the target output for all modes and the actual output d, seeking on the gradient $\nabla f(W_k)$ and descent direction $d_k = \nabla f(W_k)$ of each node. Fourth, correcting weight vector of each node, then introducing momentum factor, so it is $W_{k+1} = W_k + \eta d_k + \alpha \Delta \omega$, turning second. Fifth, it is the end. The BP algorithm of BP neural network is currently the most common type of neural network training [15], its advantage is accuracy and has a self-

learning ability. Arithmetic of Back Propagation network is shown in figure 2.

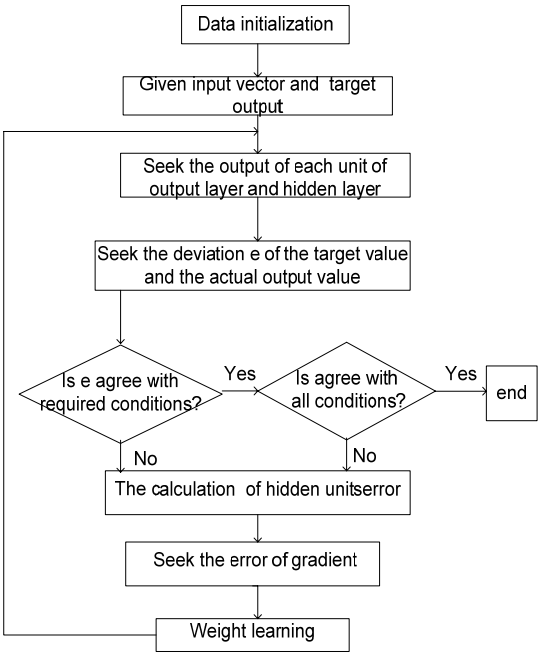

Figure 2. Arithmetic of Back Propagation network

The specific learning process of BP neural network as Follows:

(1) Input mode sequence spread

This process mainly calculated its actual output using the corresponding input mode, we assume the input vector $A_k=[\alpha_1^k,\alpha_2^k,\cdots\alpha_n^k]$, $k=(1,2,...,m)$, in which , m is Learning mode the number , n is input layer unit. We assume the output mode vector $Y_k=[y_1^k,y_2^k,\cdots y_q^k]$, in which q is the output layer unit number, the middle layer neuron activation values is

$$s_j=\Sigma w_{ij}\bullet a_j-\theta_j(j=1,2...,p) \tag{1}$$

w_{ij} , the connection weights of Input layer to middle layer:

θ_j , it is the unit threshold of middle layer;

p , it is the middle layer unit number

Activation function using the continuous differentiable S-type function,

$$f(x)=1/[1+\exp(-x)] \tag{2}$$

The output of middle layer unit j is

$$b_j=f(s_j)=1/[1+\exp(-\sum_{i=1}^{n}w_{ij}\bullet a_j+\theta_j)] \tag{3}$$

At the same time, θ_j is also constantly being revised in the learning process like the weight and the same value.

We set the activation value of the output layer of the t-unit z , then

$$l_t=\sum_{j=1}^{p}v_{jt}\bullet b_i-r_t \tag{4}$$

We set the actual value of the output layer of the t-unit c_t , then

$$c_t=f(l_t) \tag{5}$$

v_{jt} , the connection weights of middle layer to input layer:

r_t , is the unit threshold of output layer

$f(\bullet)$, S-type activation function

(2) Back-propagation of output error

The correction error of output layer:

$$d_l^k=(y_l^k-c_l^k)f'(l_l^k) \tag{6}$$

$l=1,2,...q$, $k=1,2...m$

y_l^k ,hope output

c_l^k ,actual output

$f'(\bullet)$, the derivative of the output layer function

The correction error of middle layer unit,

$$e_j^k=(\sum_{i=1}^{q}v_{jt}\bullet d_l^k)f'(l_l^k) \tag{7}$$

$j=1,2,...,p$, $k=1,2,...,m$

The correction of connection weights of output layer to the middle layer and output layer threshold is:

$$\Delta v_{jt}=a\bullet d_t^k b_j^k \tag{8}$$

$$\Delta r_i=\alpha\bullet d_t^k \tag{9}$$

b_j^k ,it is output of the middle layer unit j

d_t^k ,it is the correction error of output layer.

$j=1,2,...,p$, $t=1,2,...q$, $k=1,2,...,m$, $0\langle\alpha\langle 1$ (learning coefficient)

The correction of middle layer to the input layer is:

$$\Delta w_{ij}=\beta\bullet e_j^k\bullet a_i^k \tag{10}$$

$$\Delta\theta_j=e_j^k \tag{11}$$

e_j^k ,The error correction of the middle layer unit j

$i=(1,2,...,n)$, $0\langle\beta\langle 1$ （Learning coefficient）

(3) Cycle memory training

For each group of BP neural network input training pattern, it has to cycle and memory hundreds or even million times training to make the error of network output become small and in order to make the network to remember this model.

III. COAL AND GAS OUTBURST BP NEURALNETWORK MODEL

A. Factors of Affecting Coal and Gas Outburst

The key of the establishment of coal and gas outburst BP neural network model is to determine the characteristics indicators of reflecting the gas outburst mine [6]. We establish the coal and gas and outburst neural network model on the basis of analyzing the Jiaozuo coal and gas outburst regulation and collecting the highlight data of east mine in Jiaozuo over the years.

B The Geological Characteristics of Coal and Gas Outburst

(1) Geological structure. Coal and gas outburst has a close relationship with the mine geological structure, in general [11], geological changing areas are prone to outburst, More outburst occur in the pressure or pressure-shear fault, development zones anticline axis and rapidly changing parts of the coal occurrences. The highlighting number is accounting for 85% in the geological structure of east mine in Jiaozuo.

(2) Coal seam thickness. Coal and gas outburst are likely to occur at the part of coal thickness changing and especially the area when thin coal seam enter the thickness coal seam [13].

(3) Coal seam inclination changes. The parts of the coal seam dip changes are prone to break out; it is the result of the weight of coal besides other conditions.

(4) Soft layered in coal. Intense destructed soft coal is to prone outburst easily when the roadway entering the site It would change the flexibility of coal and rock with the rapidly expanding gas release because the value of f is very small and easily broken.

(5) Physical and mechanical properties of coal and coal structure. The damage extent of coal structure may reflect the required energy rank about the highlight; On the other hand, it also reflects the gas adsorption rate. The destruction of coal types is divided into five categories in "Rules". From the mine over the years, the destruction of coal and gas outburst type often is the type of Ⅲ, Ⅳ, and Ⅴ. Indicators of the coal characteristics structure are crumpled coefficient k, gas emission index of Δp, coal robustness factor f.

C. Dynamic Characteristics of Drilled Gas

We can see that coal and gas outburst is always accompanied with power phenomena. These phenomena are one basis that we predict the coal and gas outburst. It usually has the following rules: the pressure tunnel roof, dregs, coal-gun sound, sound of muffled thunder. Gas concentrations suddenly big or suddenly small, the increasing pressure gas of the top drill, sticking and other conditions. It is found that not all the warnings appear at the same time, there is often only one or a few warnings and some are not obvious.

D. The Sensitivity Indicators of Outburst

The sensitivity indicators of outburst are the quantitative indicators of coal and gas outburst prediction. According to the mine actual situation and then we determine a reasonable predictor and the threshold.

E. BP Neural Network Model of Coal and Gas Outburst

Input parameters are the main factors which affect prominent, because the outburst itself is a complex dynamic process [18]. There are many different factors from region to region affecting the outburst. However, the number of prediction parameters for neural network is not great for its impact. They only increase the number of input neurons and make the speed of prediction a slower decline. At the same time, too many parameters will lead to difficulties of parameter determination in the practical application.

For a multi-layer networks, Selecting the several hidden layer, Hecht-Nielsen has proved that we use one hidden layer network to approximate for any closed interval of a continuous function. Based on a three-tier BP algorithm we can complete the mapping from any n-dimensional to m-dimensional [7].

We analyze the influencing factors of coal and gas outburst on the head. We judge by the coal geology, drilling gas dynamic characteristics and sensitivity indicators of highlight. We should exclude some unreliable data sources when we establish prediction models in order to reduce system size and decrease the learning of the system and complexity. We select the geological structure, coal seam inclination changes and other 4 indicators as the input layer neurons of neural network. A hidden layer nodes is 35 and the output layer nodes is 2. The number of nodes of coal and gas outburst BP neural network model is 4, 35 and 2.

F. Training Sample1selection

At the same time, kolmogorow mapping neural network existence theorem shows that it accurately realize a three-layer neural network for any continuous function or mapping [14]. The input layer of neural network have n neurons and hidden layer have 2n+1 neurons, We select the measured data of 15 typical outburst domestic to train and learn the sample set for the neural network model. Learning and training of Neural network converge through the iterations, and the network fully and accurately identify the learning sample [9]. We establish a complex non-linear mapping relationship level between the influencing factors and outburst strength. Training samples predict value by coal and gas outburst record information over the years, including geological features of the salient points, the warning of highlight, prominent position (roadway, uphill), and Shimen exposing coal. We select two representative salient points to make forecasts more accurate. They are good samples to learn and memory. The first training sample is shown in TABLE Ⅰ.

G. The Normalization Process of the First Sample Data

We encoded some qualitative indicators in training sample parameters. The output layer (1 0) said prominent;

the output layer (01) non-prominent. Salient points of the input layer tunnel type (100) said Lane, The destruction type III,IV and V of the coal is 1. The destruction type I and II of the coal is 0.

TABLE I.
THE FIRST TRAINING SAMPLE FOR COAL-GAS-OUTBURST

Number	Lane	Inclined	Coal thickness	Dip/。	Shooting	Gas changes	Drilling	Vertical depth/m	Network output
1	1	0	1	40	1	1	0	520.1	10
2	0	1	0	30	0	1	1	665.0	10
3	0	0	0	35	0	1	0	700.3	01
4	0	1	1	27	0	1	0	975.1	01
5	1	0	0	29	1	1	1	710	10
6	0	1	1	25	0	1	1	708.2	10
7	0	0	1	15	0	1	1	922.0	01
8	0	1	1	35	1	1	1	793.2	10
9	1	0	0	29	1	1	1	850.2	01
10	1	0	1	25	0	1	1	956.1	10
11	1	0	1	24	0	1	1	633.1	judge
12	0	0	0	26	1	1	0	784.1	judge
13	0	1	1	25	0	1	1	658.4	judge

H .Prediction Model Training

The first training sample come from mine coal and gas outburst examples. TABLE I selects 12 samples for training, Average error of design system is 0.0001.Momentum coefficient is 0. 9, $SSE=9.60695e—005$, Training times of *epoch* is 687. It can be seen from TABLE Ⅰ that sample learning output error is very small. The high precision is shown in TABLE II.

TABLE II.
THE RESULT OF THE FIRST TRAINING SAMPLE

Number	1	2	3	4	5	6	7	8	9	10
Network output before training	1	1	0	0	1	1	0	1	0	1
	0	0	1	1	0	0	1	0	1	0
Network output after training	0.9990	0.9994	0.0000	0.0030	0.9995	0.9979	0.0012	0.9965	0.0034	0.9977
	0.0011	0.0006	1.0000	0.9966	0.0018	0.0021	0.9987	0.0033	0.9964	0.0023
Prediction accuracy	99.8%	99.9%	100%	99.7%	99.8%	99.8%	99.8%	99.7%	99.7%	99.8%

I. Identification of Coal and Gas Outburst Working Face

The trained samples1-10 identify coal-gas-outburst of working face 11-13. The results is shown in TABLE Ⅲ.Working face12 has the risk of outstanding. Working face12-13 has no risk of outstanding. The model identification is consistent with the actual.

TABLE III.
THE IDENTIFICATION FOR COAL-GAS-OUTBURST OF THE FACE

Number	11	12	13
Network output before training	0	1	0
	1	0	1
Network output after training	0.0236	0.9972	0.0188
	0.9965	0.0027	0.9421
Prediction accuracy	97.6%	99.7%	98%
Outburst identification	No outburst	Outburst	No outburst

J. Training Sample 2 Selection

We choose another a representative salient point, in order to facilitate learning and memory the sample and increase forecast accuracy .The second training sample come from the mining of coal and gas outburst ever recorded information over the years. The second sample is shown in TABLE Ⅳ.

We select a total of 18 network learning sample that come from the mine which have the record of outburst information in the history and don't have the record of outburst information in the history. The design of the network training times *epoch* are1500. Network Performance function value *mse* is $1e-3$ .We use the BP played back fast training function trainer algorithm.

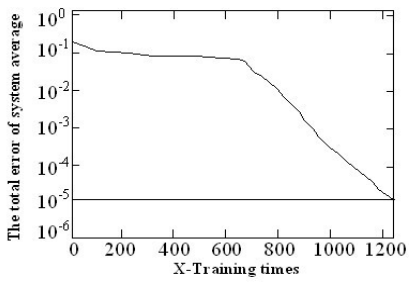

Figure 3 The error curve of Network train

TABLE IV.
THE SECOND TRAINING SAMPLE FOR COAL-GAS-OUTBURST

Number	Lane	Inclined	Coal thickness	Dip/。	Shooting	Gas changes	Drilling	Vertical depth/m	Network output
1	1	0	0	37	0	1	0	520.1	10
2	0	0	1	32	1	1	1	665.0	10
3	1	0	1	28	1	1	0	700.3	10
4	0	1	0	30	1	1	0	975.1	10
5	0	1	0	25	1	1	1	710	01
6	0	0	1	30	1	1	1	708.2	10
7	1	0	0	18	1	1	1	922.0	10
8	0	1	1	33	1	1	1	793.2	10
9	1	0	1	45	1	1	1	850.2	01
10	0	1	0	25	0	1	1	956.1	10
11	1	0	1	24	1	1	1	633.1	10
12	1	0	0	36	0	1	0	784.1	10
13	0	1	1	25	0	1	1	658.4	01
14	1	0	0	30	1	1	1	785.3	10
15	1	0	1	23	1	1	0	669.2	10
16	0	1	1	44	0	1	1	593.4	01
17	0	1	0	42	0	1	0	685.2	10
18	1	0	1	30	1	1	1	586.7	10

After learning, the training results in figure 3, $SSE=9.85282e—006$. Training times of $epoch$ is 1213. The comparison of sample learning result and the actual results is shown in the TABLE Ⅴ.

TABLE V.
THE LEARNING RESULT OF THE SECOND SAMPLE

Number	1	2	3	4	5	6	7	8	9
Network output before training	1	1	1	1	0	1	1	1	0
	0	0	0	0	1	0	0	0	1
Network output after training	1.0000	0.9934	1.0000	0.9970	0.0023	1.0000	1.0000	1.0000	0.0048
	0.0000	0.0041	0.0000	0.0018	0.9985	0.0000	0.0000	0.0000	0.9967
Prediction accuracy	100%	99.5%	100%	99.7%	99.8%	100%	100%	100%	99.6%
Number	10	11	12	13	14	15	16	17	18
Network output before training	1	1	1	0	1	1	0	1	1
	0	0	0	1	0	0	1	0	0
Network output after training	1.0000	1.0000	0.9904	0.0085	1.0000	1.0000	0.0000	1.0000	1.0000
	0.0000	0.0000	0.0062	0.9939	0.0000	0.0000	1.0000	0.0000	0.0000
Prediction accuracy	100%	100%	99.2%	99.3%	100%	100%	100%	100%	100%

As can be seen from TABLE Ⅴ, sample learning output error is very small and has high precision (average reach 99.8%). We select five real samples (all parameters are shown in TABLE Ⅵ). We use the BP network of coal-gas-outburst which has been well learned to predict the result. The result is shown in TABLE Ⅶ.

TABLE VI.
COAL-GAS-OUTBURST PREDICTION SAMPLE OF BP NETWORK

Number	Lane	Inclined	Coal thickness	Dip/。	Shooting	Gas changes	Drilling	Vertical depth/m	Network output
1	0	1	1	55	0	1	0	659.3	10
2	1	0	0	23	1	1	0	632.1	10
3	1	0	1	30	0	1	1	690.2	01
4	1	0	0	25	0	1	0	740.5	10
5	0	1	1	20	1	1	1	821.3	01

TABLE VII.
NETWORK PREDICTION RESULT

Number	1	2	3	4	5
Network output before training	1	1	0	1	0
	0	0	1	0	1
Network output after training	1.0000	1.0000	0.0000	0.9970	0.0240
	0.0000	0.0000	1.0000	0.0018	0.9810
Prediction accuracy	100%	100%	100%	99.7%	97.8%
Outburst identification	Outburst	Outburst	No outburst	Outburst	No outburst

We use the method based on artificial neural network model for improved prediction of gas emission described in this paper, it is improved that this method is very correct and it also has a high precision.

IV. CONCLSION

(1) They have a complex non-linear relationship among the coal and gas outburst, geological features, gas dynamic phenomena and sensitive indicators. Artificial neural network learn and memory various factors of coal and gas outburst [16], overcoming the shortcomings of using a single sensitivity indicators and highlight warnings to judge subjectively, making experience and decision quantitative and scientific [10]. Forecasting in the field, as long as all kinds of indicators and parameters enter into the computer, the results can be obtained. So people use artificial neural networks to study outburst having a very broad application prospects.

(2) The key of coal and gas outburst neural network is to identify the selection of training sample and the extraction of prominent feature value. The prominent indicators are determined according to specific conditions of the mine, continuing to absorb new samples, making the maximum and minimum value of the neurons samples to be identified included in the training samples. This will enable higher recognition accuracy.

(3) Because of highly irregular and greater volatility of the some production monitoring data, it makes the direct use of neural network prediction method to be difficult to meet the accuracy request. This design of artificial neural network prediction performance is generally satisfied, and it also has a better analysis of the relationship between the various factors affecting gas content and the quantitative.We combine with the coal and gas outburst basic theory and artificial neural network and other modern high-tech together [12].We predict the gas on the base of artificial neural network theory and other modern high-tech together. We are able to solve the problem of coal-gas-outburst prediction. The method is feasible and provides a new idea for the further development for the further development.

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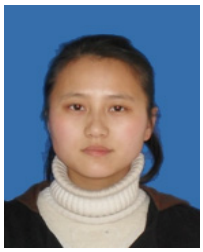

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