MSc Thesis

Prediction of Methane Emission Quantity Based on Back- Propagation Neural Network

Author: Yuchen Fan

Supervisor: Professor Hongqing Zhu

Date(04/06/2018)

School of Resources and Safety Engineering
China University of Mining and Technology (Beijing)

Beijing Haidian district Xueyuan Rd,Ding 11.
Zonghe Building 225

Declaration of Authorship

„I declare in lieu of oath that this thesis is entirely my own work except where otherwise indicated. The presence of quoted or paraphrased material has been clearly signaled and all sources have been referred. The thesis has not been submitted for a degree at any other institution and has not been published yet."

Abstract

In recent years, the number of gas accidents in China's coal mines has declined year by year. However, coal mine gas accidents often cause group deaths and injuries, resulting in a high mortality rate of gas accidents. Gas disasters seriously restrict the safety production of coal mines in China and effectively control the occurrence of gas disasters. It is of great significance to improve the safety production management of coal mines in China. This paper takes the 81505 working face of Baode Mine in Shendong Mining Area as the main research object. Based on the coal mine's historical monitoring data, the BP neural network is used to predict the methane emission from the working face. In the previous part of the thesis, the main influencing factors of methane emission from the working face were theoretically analyzed, an index system for the influencing factors of methane emission from the working face including 16 third-level indicators was established, and the methane emission from the working face was calculated using the method of grey correlation analysis. The correlation degree of each influencing factor indicator, the calculation result shows that the correlation coefficient of the 16 influencing factor indicators of the gas emission amount of the working face is above 0.6, and all of them have a strong correlation with the methane emission amount of the working face. The forecasting results show that the prediction model of methane emission quantity with 12 nodes in the hidden layer is the best. The prediction of the gas emission quantity of the 81505 working face using the optimal model is 4.906 m3/min, which basically accords with the actual situation of the coal mine. The research results provide reference for the prevention and control of gas hazards in coal mines.

Keywords Fully-mechanized face, methane emission prediction, BP neural network

Content

1 Introduction

In recent years, although the coal mine safety situation in China has generally improved, the total number of safety accidents and deaths caused by coal mine accidents is still very large（Yin Wentao, et al 2013）.There is a large gap between the safety level of the coal industry and developed countries such as Europe and the United States. China's coal mining conditions are complex. Coupled with the lack of infrastructure for safe production, gas disasters are a major challenge for coal production. Gas disaster prevention and control is the most important task for coal mining and production. At present, the major gas disasters in China's coal mine safety production are methane explosions and coal and methane outbursts.

1.1 Background and significance of this research

The author has obtained statistics on accidents and deaths of gas explosions in coal mines in China during the recent five years from 2013 to 2017（Yin WenTao, et al 2013）, as shown in Figure 1 and Figure 2, from the statistics of the accident online inquiry system of the State Administration of Work Safety. At present, there are an average of 10,000 coal mines in China. From the map, the annual gas explosion accidents and the number of coal and gas outburst accidents are relatively insignificant, and they are declining year by year. In particular, no coal occurred in 2017. With the gas outburst accident, this shows that with the advancement of science and technology, China's coal mine safety management level is gradually increasing. However, it can also be seen from the figure that the mortality caused by these two types of gas accidents is very high, especially gas explosions, which often cause group bodily deaths and injuries.

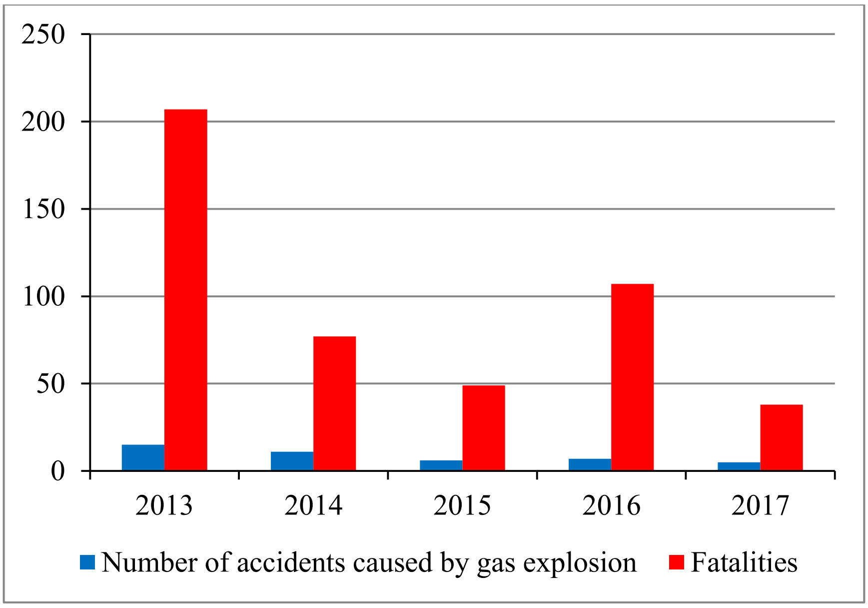


Figure 1 Gas explosion accidents and deaths from 2013 to 2017

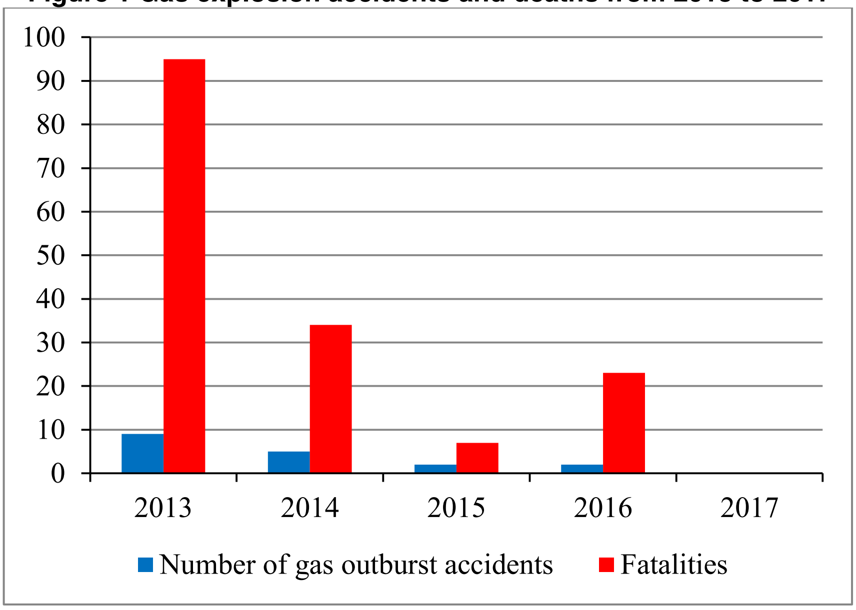


Figure 2 Gas outbursts and deaths from 2013 to 2017

Methane emission prediction is the basic work for mine gas control work and provides a reference for mine ventilation optimization and gas control measures. For the face of high methane mines, there is a large relationship between methane emission volume and production volume. Through the prediction of methane emission volume, an effective analysis of gas hazard levels at the working face can be made, so that labor organization procedures can be more reasonably arranged to ensure safe production.

The Baode Mine studied in this paper is a typical high-methane coal mine, and the gas control work is the most important task for coal mine safety production management. It is necessary to forecast the methane emission in the working face. After more than ten years of mining, Baode Mine has accumulated a large amount of methane-related data. The paper will rely on these historical methane data to take the Baode Mine 81505 working face as an example, based on the artificial neural network and the amount of methane emission from the working face to do the study.

1.2 Research status of home and aboard

The prediction of methane emission began in the 1960s. Soviet coal scholars proposed the prediction of methane emission during coal mining and put forward corresponding prediction specifications. Subsequently, some of the world's coal powers have also proposed some methods for predicting the amount of gas emission, such as the British Allefa（1968）, the West Susutitz Act, the Soviet Institute of Mining Research, Bazenysky, and Makenifa (1989). , statistical methods，etc.

1.2.1 Prediction of methane emission volume study of home and aboard

The prediction of methane emission in China is usually based on mine statistics, sub-source prediction（Lin Boquan, et al 2014）, and coal seam gas content method. Mine statistics is based on the historical statistics of methane emission from the mining area of the mine and use linear regression is used to estimate the methane emission in other areas. For example, Huang Ming (2014) used mine statistics to predict the methane emission from the 5-3 coal seam of Faer Mine. The positive correlation between methane emission and depth was found. The sub-source prediction method is to rationally divide the source of methane emission from the working face, calculate the methane emission quantity from each source separately, and finally calculate the methane emission quantity from the working surface. For example, Xu Tao et al. (2009) calculated the methane emission volume of a new mine using the sub-source prediction method. The gas content method uses the original gas content of the coal seam and the post-harvest residual gas content to calculate relative methane emission.

Regarding the forecast of methane emission, some scholars have used neural network model to make relevant researches. However, during the forecasting process, the influencing factors of methane emission are not considered comprehensively, resulting in too few impact indicators and lack of certain scientific nature.

1.2.2 Research of BP- Neural network of home and aboard

Neural networks were invented in the 1940s. The artificial neural network algorithm responds to input information by simulating the structure and function of the human brain（Airey. E. M 1968）. The network structure includes an input layer, an intermediate hidden layer, and an output layer. In practical applications, some training data are first selected for autonomous learning to form knowledge and laws, and then the target data is analyzed, predicted, and classified. Because neural networks have the ability to deal with non-linear mapping problems, they are widely used in variable prediction problems. Domestic and foreign scholars have made a lot of research on improving and optimizing neural networks.

For example, Wang Lei et al (2016)proposed to improve the BP neural network algorithm by dynamically increasing the number of hidden layers, and improve the convergence speed and generalization ability of the network; Huang Shangqing et al（2017）aims at the shortcomings of slow convergence when training large samples for BP neural networks, using the improved cross batch gradient descent algorithm to train, the convergence speed of network training has been significantly improved; Saima et al.（2013） proposed the use of variance-covariance method to adjust the weights in the neural training process, thereby improving the network's prediction accuracy; Siswantoro（2016） proposed a method to improve classification performance of neural networks by constructing a linear model based on Kalman filter as post-processing, transforming the prediction output of neural networks by using a linear combination of object features and prediction output. To approach the expected output value, such conversion reduces the neural network error and improves the classification performance. Sheng X. (2017) proposed a new error function to improve the neural network learning algorithm. Experimental results show that the improved algorithm can converge to error accuracy at a faster speed. Vano Oyen (1943) modified the total error performance function in the neural network error back propagation algorithm, making the algorithm simpler and improving the learning speed of the network.

1.3 Main research content of this paper

In this paper, the gas emission volume in the 81505 face of Baode Mine is studied. Theoretical analysis and numerical simulation are the main research methods. The BP neural network is used to predict the amount of gas emission. The main research content includes the following aspects:

(1) Introduce the principle of neural network algorithm, structure composition, type of activation function, learning rules and methods of neural network, steps of model establishment. Explain the prediction principle of BP neural network.

(2) Analyze the sources of methane emission in the fully mechanized coal mining face, analyze the influencing factors of methane emission from the aspects of geological structure, mining process, production technology and natural environment, determine the quantifiable factors, and finally establish the data indicator system of the influencing factors of methane emission.

(3) According to the data index system of the influencing factors of methane emission from working face, the relevant data of methane emission quantity were collected to build a neural network training sample.

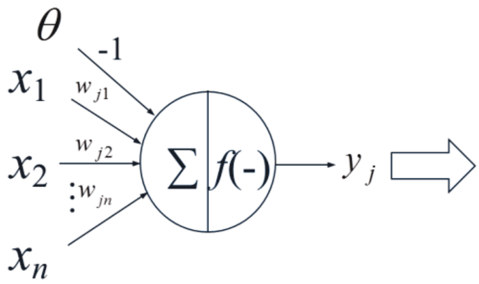
(4) Establish a BP neural network prediction model for the amount of gas emission from the working face, and select the optimal model through training. The optimal model was used to predict the gas emission from the working face and error analysis was performed.

2 Neural network prediction model

Artificial neural network has been invented since the 1940s. After more than 70 years of development and improvement, it has been widely used in engineering, medical, transportation, economics, and big data analysis and processing.

2.1 Mathematic model

Neurons are the basic units of neural networks. A neural network consists of many neurons. A neuron contains multiple inputs and corresponds to one output, which has a complex calculation function inside. Figure 3 shows a typical neuron model.



$$y_j(t) = f(\sum_{i=1}^{n} w_{ji}x_i - \theta_j)$$

Figure 3 Neuron model diagram

In the figure, θ_j represents the threshold, w_{ji} represents the connection weight coefficient, n is the number of input components, x_i represents the input component, y_i represents the output of the neuron, and f(-) represents the activation function. The entire transfer process can be expressed as: At the beginning, the size of the transmitted signal component is still x_i, and the weighted parameter w_{ji} is in the middle. After this weighted signal becomes $x_i w$, the sum of all components and the threshold θj are as the activated function input.

The use of neuron models can be understood as follows: suppose there is a data set, called a sample, assuming that the characteristics of the sample can be described with three variables. There are now two variables X_1 and X_2 with known eigenvalues, and the other the eigenvalue of the variable Y is unknown, and the eigenvalue of Y needs to be predicted by the neuron model. The predicting process is to establish a mapping relationship between X_1, X_2, and Y by recording a set of variable eigenvalues (including X_1, X_2, and Y), and obtain the relationship weights between them. The resulting mapping is used to compare the eigenvalue of variable Y in new samples to make a prediction.

2.2 Activation function

In the artificial neural network, the activation function of the neuron node defines the mapping of the neuron output. In simple terms, the output of the neuron is processed by the activation function and then used as the output. The activation function is to handle the nonlinear mapping between input and output. Commonly used activation functions include threshold-type activation functions, Sigmoid activation functions, and the linear or piecewise linear activation.

2.2.1 Threshold-type activation function

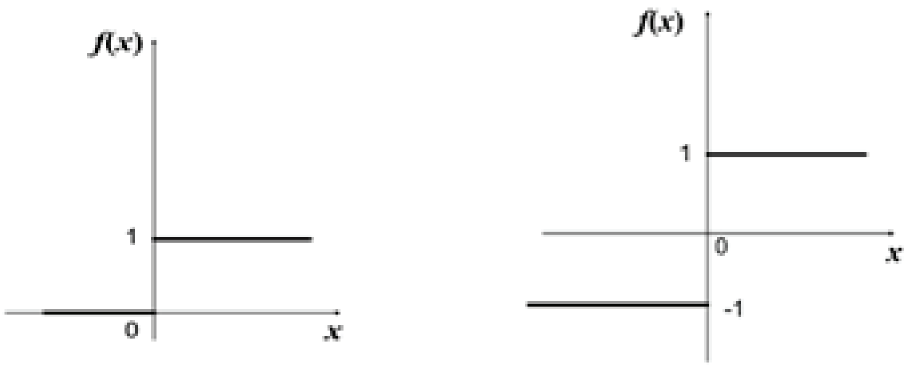
The threshold-type activation function is the simplest, and its output state is represented by only two values, taking 0, 1 or 1, and -1, representing the excitation and suppression of the neuron, respectively. Usually used for neural network classification, such as perceptron model, discrete Hopfield network, etc.

When the value is 0 or 1, it is a single-threshold type activation function whose function expression is shown in the following formula (2.1). The function image is shown in Figure 4(a).

$$f(x)=\begin{cases}1 & x\geq 0\\ 0 & x<0\end{cases} \tag{2.1}$$

When the value is 1,-1, it is a double-threshold type activation function, which is expressed in the following formula (2.2), and its function image is shown in Fig. 4(b).

$$f(x)=\begin{cases}1 & x\geq 0\\ -1 & x<0\end{cases} \tag{2.2}$$



(a) Single limit type (b) Double limit type

Figure 4 Threshold activation function image

2.2.2 Sigmoid activation function

The Sigmoid activation function is the so-called S-type activation function. The relationship between the state of the neuron and the output stage is a monotonically differentiable function in the range of (0,1). In particular, if it is a very large negative number, the output is 0; if it is a very large positive number, the output is 1. The S-type activation function is particularly suitable for the case where the feature differentiation of multiple components is more complex. It is usually applied to BP network classification problems and function approximation problems. The expression is as shown in Equation (2.3). The function image is shown in Figure 5.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2.3}$$

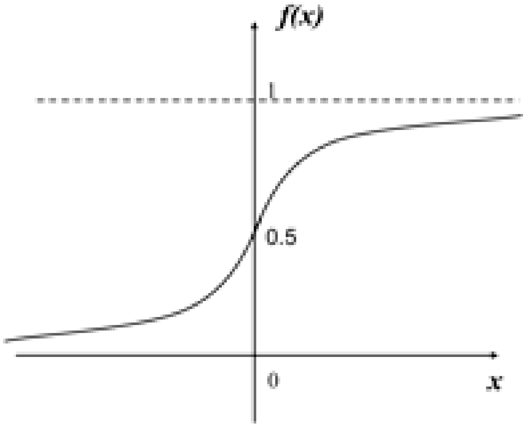
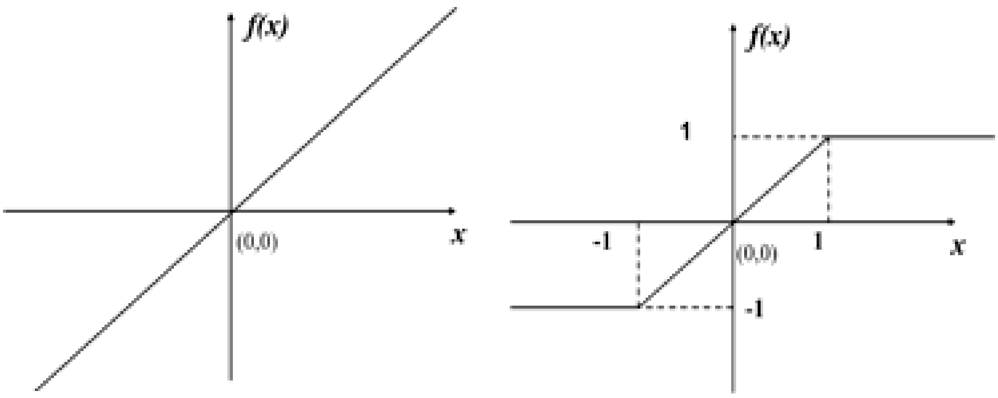


Figure 5 Sigmoid activition function image

2.2.3 The linear or piecewise linear activation

The linear or piecewise linear activation function is usually relatively simple, and a common linear function form such as f(x)=x is suitable for neural network output layer neurons that achieve function approximation. The function image is shown in Figure 6.



(a) Linear activation function (b) Piecewise linear activation function

Figure 6 Linear or piecewise linear activation function image

2.3 BP neural network model

BP (Back Propagation) neural network was first proposed by Werbos in 1976, and has been continuously improved by scholars to make its function more and more powerful. Currently, it is widely used in various fields of engineering. In this paper, the author will also adopt this network model to forecast the gas emission in fully mechanized coal mining face. BP neural network uses error back propagation algorithm. In the operation process, the error of the output layer is obtained first. Then the error of the layer above the network is estimated based on the error of the output layer. In this way, the error estimates of all other layers are obtained. It is the so-called error back propagation. In the training process, the desired goal is to minimize the sum of the squared error of the network, so from the output layer to the input layer, the error is propagated once per back-propagation, and the network will perform a correction of the connection weight and threshold between the layer and the layer, until the sum of the squared error reaches the required minimum value, then the network at this time is the optimal network for training.

2.3.1 BP neural network structure

The structure of BP neural network consists of three parts, namely input layer, middle layer and output layer. In the network computing process, the input layer and the output layer correspond to the corresponding feature components and are visible. However, the middle layer of the network is invisible. This layer has no connection with others. It is only during the network computing process that it passes through the layer. It can be said that the relationship between the input layer and the output layer is connected and adjusted by the middle layer. The middle layer is also called the hidden layer. The number of hidden layers of a neural network is not fixed. It may be a single hidden layer or multiple hidden layers. Figure 7 shows a simple BP neural network model structure diagram, which is a double hidden layer network structure. The input layer is the sample's three feature components X_1, X_2, and X_3, and the output layer includes two components Y_1 and Y_2, a first hidden layer, four nodes, and a second hidden layer, three nodes.

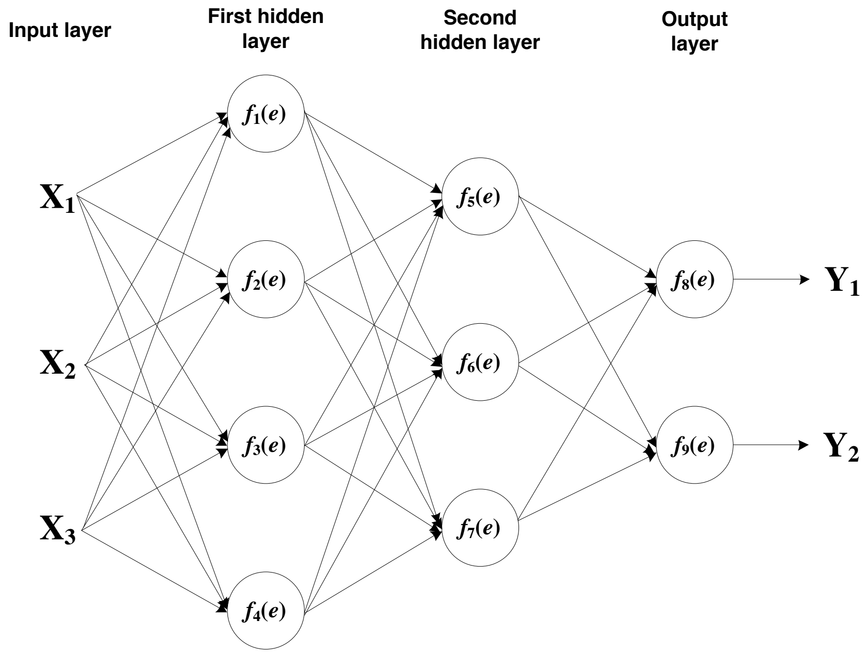


Figure 7 Structure diagram of neural network model

From the figure, it can be seen that any node in the network will form a connection with all nodes above and below it. Therefore, from the input layer to the output layer of the network, the output data of each layer will be used as the input data of the next layer. Realize the positive propagation of data.

2.3.2 Determining the number of the nodes in hidden layer

In the BP neural network, usually based on the characteristics of the research object and research objectives, the number of nodes in the input layer and the output layer of the network can be directly determined, but the number of hidden layer nodes cannot be directly determined. How the best hidden layer node number be selected is the key to obtaining the optimal model, and it accounts for a large part of the workload in the modeling process. The number of hidden layer nodes has an important influence on the performance of the neural network. It can be said that the selection of the number of hidden layer nodes is the most critical step in the process of neural network. When the number of hidden layer nodes is different, the accuracy of the prediction results obtained and the required training time vary greatly. At present, the number of hidden layer nodes can be determined by empirical formula (Jiao Licheng, et al 2016), as shown in formula (2.4), formula (2.5) and formula (2.6).

$$h = \sqrt{m+n} + \alpha \tag{2.4}$$

$$h = \log_2 n \tag{2.5}$$

$$h = \sqrt{mn} \tag{2.6}$$

h: number of hidden layer nodes;

m: the number of output layer nodes;

n: the number of input layer nodes;

α: adjustment constant between 1 and 10

In practical applications, it is necessary to select the most reasonable number of hidden layer nodes in the network training process through multiple trial and error. The most basic principle for determining the number of hidden layer nodes is to ensure the hidden layer nodes on the basis of meeting the accuracy requirements, the number is the least, because the more hidden nodes, the more complex the network, resulting in slower training and too long training time.

2.3.3 Training principle of BP neural network

The purpose of the BP neural network training is to continuously modify the connection weights so that the squared error sum of the network is minimized and the accuracy is optimal, that is, the relatively most accurate relationship between the input and the output is determined. The BP neural network training consists of two parts. The first is that the input component data is propagated forward to get the prediction data, and then the error back-propagation corrects the connection weight and the threshold. In the forward propagation process, the original input data is gradually passed to the output layer through the initial weight between layers and the transfer function. The resulting value of the output layer is the network prediction result. In the error back propagation process, the error between the predicted value and the target value of the previous step is propagated to the hidden layer through the inter-layer connection weight and transfer function, and the initial weight is corrected according to the hidden layer error. In this way, the forward propagation of data and the back propagation of errors are continuously performed until the error of one time reaches the required accuracy, and the training stops.

This paper uses a single hidden layer network as an example to mathematically derive the weights of the hidden layer and the output layer weights: Assume that (X, Y) is a sample in the sample set and O is the actual output corresponding to that sample.$X = (x_1, x_2 \ldots x_n)$, $Y = (y_1, y_2 \ldots y_m)$, $O = (o_1, o_2, Lo_m)$, w_{ij} is the weight of the *i-th* node of the hidden layer network and the *j-th* node of the input layer; θi is the threshold of the *i-th* node of the hidden layer; φ(x) is the activation function of the hidden layer; w_{ki} is the weight of *k-th* node of the output layer and the hidden layer *i-th* Node; a_k denotes the threshold of the output layer *k-th* node; ψ(x) denotes the output layer activation function; o_k denotes the output layer k-node output, k = 1, ..., L.

The entire training process is as follows:

The input of the i-th node of the hidden layer net_i:

$$net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{2.7}$$

The output of the i-th node of the hidden layer y_i:

$$y_i = \phi(net_i) = \phi(\sum_{j=1}^{M} w_{ij} x_j + \theta_i) \tag{2.8}$$

The input of the k-th node of the output layer net_k:

$$net_k = \sum_{i=1}^{q} w_{ki} y_i + a_k = \sum_{i=1}^{q} w_{ki} \phi(\sum_{j=1}^{M} w_{ij} x_j + \theta_i) + a_k \tag{2.9}$$

The output of the k-th node of the output layer o_k:

$$o_k = \psi(net_k) = \psi(\sum_{i=1}^{q} w_{ki} y_i + a_k) = \psi\left(\sum_{i=1}^{q} w_{ki} \phi(\sum_{j=1}^{M} w_{ij} x_j + \theta_i) + a_k \right) \tag{2.10}$$

The error Ep between the actual output value of an individual p in the sample set and the observation value can be expressed as:

$$E_p = \frac{1}{2} \sum_{k=1}^{L} (y_k - o_k)^2 \tag{2.11}$$

The total error of P training samples can be expressed as:

$$E_p = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{L} (y_k^p - o_k^p)^2 \tag{2.12}$$

According to the error gradient descent method, the output layer weight coefficient adjustment amount Δw_{ki}, the output layer threshold adjustment amount Δa_k, the hidden layer weight coefficient adjustment amount Δw_{ij}, and the hidden layer threshold adjustment amount $\Delta\theta_i$ are sequentially corrected.

$$\Delta w_{ki} = -\eta \frac{\partial E}{\partial w_{ki}};\quad \Delta a_k = -\eta \frac{\partial E}{\partial a_k};\quad \Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}};\quad \Delta \theta_i = -\eta \frac{\partial E}{\partial \theta_i} \tag{2.13}$$

The output layer weight coefficient adjustment amount Δw_{ki}:

$$\Delta w_{ki} = -\eta \frac{\partial E}{\partial w_{ki}} = -\eta \frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial w_{ki}} = -\eta \frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial net_k}\frac{\partial net_k}{\partial w_{ki}} \tag{2.14}$$

The output layer threshold adjustment amount Δa_k:

$$\Delta a_k = -\eta \frac{\partial E}{\partial a_k} = -\eta \frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial a_k} = -\eta \frac{\partial E}{\partial o_k}\frac{\partial o_k}{\partial net_k}\frac{\partial net_k}{\partial a_k} \tag{2.15}$$

The hidden layer weight coefficient adjustment amount Δw_{ij}:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta \frac{\partial E}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} = -\eta \frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial w_{ij}} \tag{2.16}$$

The hidden layer threshold adjustment amount $\Delta \theta_i$:

$$\Delta \theta_i = -\eta \frac{\partial E}{\partial \theta_i} = -\eta \frac{\partial E}{\partial net_i}\frac{\partial net_i}{\partial \theta_i} = -\eta \frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial \theta_i} \tag{2.17}$$

and because:

$$\frac{\partial E}{\partial o_k} = -\sum_{p=1}^{P}\sum_{k=1}^{L}(T_k^{\ p} - o_k^{\ p}) \tag{2.18}$$

$$\frac{\partial net_k}{\partial w_{ki}} = y_i,\quad \frac{\partial net_k}{\partial a_k} = 1,\quad \frac{\partial net_i}{\partial w_{ij}} = x_j,\quad \frac{\partial net_i}{\partial \theta_i} = 1 \tag{2.19}$$

$$\frac{\partial E}{\partial y_i} = -\sum_{p=1}^{P}\sum_{k=1}^{L}(T_k^p - o_k^p)\cdot \psi'(net_k)\cdot w_{ki} \tag{2.20}$$

$$\frac{\partial y_i}{\partial net_i} = \phi'(net_i) \tag{2.21}$$

$$\frac{\partial o_k}{\partial net_k} = \psi'(net_k) \tag{2.22}$$

The threshold and weight coefficient adjustments of the final hidden layer and output layer can be expressed as:

$$\Delta w_{ki} = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k{}^p - o_k{}^p) \cdot \psi'(net_k) \cdot y_i \tag{2.23}$$

$$\Delta a_k = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k{}^p - o_k{}^p) \cdot \psi'(net_k) \tag{2.24}$$

$$\Delta w_{ij} = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - o_k^p) \cdot \psi'(net_k) \cdot w_{ki} \cdot \phi'(net_i) \cdot x_j \tag{2.25}$$

$$\Delta \theta_i = \eta \sum_{p=1}^{P} \sum_{k=1}^{L} (T_k^p - o_k^p) \cdot \psi'(net_k) \cdot w_{ki} \cdot \phi'(net_i) \tag{2.26}$$

2.3.4 BP neural network modeling steps

(1) Determine the number of network layers

The input and output of a neural network are usually one layer. The number of hidden layers can be single or multiple layers. Therefore, the number of network layers is mainly to determine the number of hidden layers. In general, a three-layer network structure containing a single hidden layer is selected with a suitable number of hidden layer nodes, it can approach any nonlinear function while maintaining sufficient accuracy, so a single hidden layer structure can solve most problems.

(2) Determining the number of input and output layer nodes

The number of input layer and output layer nodes is generally determined based on the research questions and the external descriptions related to the problem. Generally, there is only one output node according to the research target, corresponding to only one output, and each input node corresponds to one component. There should be a large correlation with the output component and the input component. For example, the amount of gas emission from the working face is studied in this paper. The amount of gas emission from the working face is taken as the output, and the factors that affect the gas emission quantity and can be extracted are taken as the input component. The number of these influencing factors is the number of input layer nodes of the BP neural network.

(3) Determine the number of hidden layer nodes

The number of hidden layer nodes will directly affect the performance of the model. It is necessary to test repeatedly according to the method in Section 2.3.3 of this chapter to evaluate the learning performance of the model under different number of hidden layer nodes. The training accuracy and training time are the main performance evaluation criteria, and the final determination is made by finding the optimal number of hidden layer nodes.

(4) Determination of activation function

The activation function mainly affects the training accuracy of the model and the convergence time of the training process. The activation function is generally used in the hidden layer, and usually the sigmoid function, tansig function and logsig function are selected.

(5) Setting of training parameters

The training parameters include the maximum allowed number of training steps epochs, the training target minimum error goal, the learning rate lr, the interval step number show, and the momentum factor mc for each displayed training result. These parameters need to be set in advance before the model training.

(6) Determination of training function

Different training functions represent different algorithms of the network, and training functions have a great influence on the training time of the network. The commonly used training functions are mainly as the following:

(1) Trainlm function: Levenberg-Marquardt algorithm is adopted. The remarkable feature of this algorithm is that the convergence speed of the training process is fast, and it is also the default algorithm of the neural network in most software platforms. However, it requires the computer to have a large amount of memory.

(2) Traingdm function: The momentum gradient descent function is used. The obvious advantage is the faster convergence speed. In addition, because the influence of the momentum factor is taken into account during the algorithm, the local minimum problem is avoided.

(3) Trainrp function: using the BP algorithm with rebound, with a faster training speed.

(4) Trainbr: Adopts the Bayesian-Regularization algorithm. The training algorithm can improve the generalization ability of the network, so that the network has better classification and identification capabilities, and it is more conducive to the identification of the optimal network, and it is also widely used.

After the model is built according to the above steps, the network model can be trained and learned by reading the sample data. The model accuracy can be adjusted by adjusting each parameter to obtain the optimal model, which can then be used for the analysis and prediction of practical problem.

3 Study on the influencing factors of methane emission quantity at fully mechanized working face

During the development and production of mines, the methane inside coal and rock bodies seeps through the exposed surface of the coal and rock to the well and roadway space. This is a macroscopic manifestation of methane emission, and there are many influencing factors in methane emission. Accurate gas analysis of the source and the amount of methane so that it can provide powerful technical support for mine gas control. Based on the neural network prediction of methane emission in fully mechanized coal mining face, the impact indicators of methane emission from the fully mechanized coal mining face must first be determined, which will lay the foundation for the subsequent data collection. Therefore, this chapter mainly studies the influencing factors of the fully mechanized coal mining face.

3.1 Methane emission mechanism in fully mechanized working face

3.1.1 Methane in coal seam reserves

The adsorption characteristics of coal are very strong, so there is a lot of gas in the coal. In general, the gas(methane) in the deep coal seam will slowly diffuse from the relatively closed space of the coal body to the ground, while the air on the ground will spread to the underground coal seam in the direction of the vertical ground, so the gas in the coal seam is distributed perpendicularly to the ground. Gas in the coal seam will exist in both the adsorbed state and the free state, so the gas content of the coal seam includes the sum of the adsorbed gas amount and the free gas amount. Coal molecules and gas molecules are physically adsorbed by van der Waals forces. When certain conditions are met, gas can also be desorbed from the coal. The volume of adsorbed gas in coal can usually be calculated according to formula (3.1):

$$X_y = VPT_0 / (TP_0\xi) \qquad (3.1)$$

V—the pore volume of unit weight coal, m3/t;

P -gas pressure, MPa;

T_0, P0-standard conditions;

T -gas absolute temperature, K;

ξ-gas compression factor;

X_y—free gas content of coal under standard conditions, m^3/t

The free gas content of coal can usually be calculated according to equation (3.2):

$$X_x = \frac{abP}{(1+bP)} e^{n(t_0 - t)} \frac{1}{(1+0.31W)} \times \frac{(100-A-W)}{100} \qquad (3.2)$$

Where: a, b - adsorption constant;

P---coal gas pressure, MPa;

t_0---the temperature at which the laboratory tests the adsorption constant of coal, °C;

t---coal temperature, °C;

n---Correlation coefficient;

A---ash content in coal, %;

W---coal moisture, %;

X_x---adsorption gas content of coal, m^3/t (under standard conditions).

The main factors affecting the amount of adsorbed gas include the coal gas adsorption capacity, gas pressure in the coal body and coal body temperature (Yan Hong,et al 2009). In general, there is a positive correlation between coal gas pressure and gas content. If the coal gas pressure is greater, then the gas content is higher; when the pressure gas is certain, the coal gas content will decrease as the temperature increases. Experiments show that when the coal gas pressure reaches 5MPa, the amount of adsorbed gas will tend to be saturated.

3.1.2 Methane emission source of fully mechanized working face

In the normal production process of the fully mechanized coal mining face, most of the gas in the coal body will be in a relatively stable state, which will flow out from the surface of exposed coal wall or cracks through a gentle flow form, and will also flow out from the broken coal. Gas outflows usually have two forms of expression: absolute gas emission (in m^3/min) and relative gas emission (in m^3/t), which can be transformed into each other. According to the theory of sub-source prediction, the source of gas emission from the fully mechanized coal mining face includes the following aspects:

(1) Coal seam gas emission quantity from working face

The gas emission from the coal seam mainly comes from the gas from the exposed coal wall at the post-harvest working face, the methane from the cut coal during coal mining by the coal miner, and the coal that has fallen in front of the working face. In addition, it should be noted that in the longwall retreat type full-mechanized mining face production system, there is also an exposed roadway coal wall in the working face and return airway. Theoretically, there will be a part of the gas gushing, but when the face is cut from before the eyes are officially mined, the intake and return airways have already undergone a long preparation period. The exposure time of the roadway coal wall basically exceeds the period of gas emission and exhaustion, and the coal wall gas emission rate is extremely small. Therefore, the amount of gas emission from this part is not included in the study. In the above three parts of gas emission, the gas emission from the coal face of the working face has a negative exponential relation with the exposure time of the coal wall. The longer the time is, the smaller the gas emission is. During the process of coal mining machine, the amount of cut coal gas gushing is mainly affected by the coal crushing degree, coal shearer coal cutting speed, and the output of the working face. The gas emission amount of coal falling in front of the working face mainly depends on the residence time of coal in the front. It is related to the transport capacity of the scraper conveyor, in which the coal wall methane emission from the working face accounts for most of the gas emission from the mining layer (Shen Huayu, et al 2008).

(2) Gas emission quantity from working face adjacent layer

When there are multiple layers of coal seams in the mine, the coal seam group mining will be involved. Under normal circumstances, gas will be stably present in coal and rock. When a layer in a coal seam group can be used for coal mining, the adjacent upper and lower coal seams adjacent to this layer will be affected by mining and pressure relief will occur. The permeability of surrounding rock of coal seams and roof and floor slabs increases, and cracks that connect the mining face and the goaf may even appear between the layers (He Huaping,2015). This directly results in the desorption of large amounts of gas in the adjacent layers and floods to the mining face and goaf. The amount of gas outflow in the adjacent layer is mainly affected by the surrounding rock stress. The influence of mining on the surrounding rock stress changes, and the amount of gas emission in adjacent layers also changes with certain rules. During the mining process, the mining stress influences the distribution of stress in the top and bottom areas of the working face as the stress concentration zone, the pressure relief zone and the stress recovery zone. Correspondingly, gushing reduction, rising and falling zone will be formed in the gas emission process in the adjacent layer. The most important aspect of determining the gas emission from the neighboring layer is the first weighting of the main roof. In general, the surrounding rock of the mining layer is basically in a stable state and the gas is difficult to infiltrate before the old roof comes under pressure and before it falls. Therefore, it is difficult for the gas in the adjacent layer to affect the gas emission amount at the working face. Once the main roof is pressed for the first time, a certain gas channel will be formed between the mining layer and the adjacent layer, and will be decompressed by the mining. The original gas in the adjacent layer will be fully desorbed and discharged, so that the gas in the adjacent layer will be diffused to the working face, in which the gas diffusion rate is affected by factors such as the spacing between layers, the properties of the rocks between the layers, and the length of the mining face of the working face.

(3) Gas emission quantity from the goaf in working face

The amount of gas emission from the goaf also comes from three aspects: the first is the amount of gas that comes from the upper and lower adjacent layers of the goaf through the cracks after being affected by mining, and the second is the loss of coal and coal from the goaf. The third is the amount of gas emitted from the surrounding rock in the goaf. In the goaf, a part of the coal was lost from the part of the coal that was not recovered and was left behind. The other part was the coal pillar left over from the goaf. Generally, for thick coal seam mining, coal mines mostly use top coal mining technology. Due to factors such as mining methods and coal quality conditions, the mining face ratio is relatively low, and the coal loss in the goaf area is relatively large ,therefore the outflow of the gas is relatively large.

3.2 Influencing factors of gas emission in fully mechanized working face

Considering the technological process of coal mining comprehensively, the gas emission from the working face is mainly affected by four factors: geological factors, mining factors, production technology and natural factors (He Yuxiong, 2015). The following analysis will be carried out from these four aspects to establish index system for the impact of methane emission volume in fully mechanized mining face.

3.2.1 Geological factors

(1) Raw gas content of mining coal seam and adjacent layer

According to the analysis of the gas emission mechanism in the working face, the exploitation of coal seam gas and adjacent layer gas is the source of gas emission from the working face. Therefore, the original gas content in the production layer and adjacent layers will directly affect the gas emission amount from the working face (Cui Hongqing, et al,2015). Generally speaking, the higher the gas content of the coal seam being extracted, the greater the amount of gas diffuses per unit time, and the greater the amount of gas emission from the corresponding working face. Affected by mining, the gas from the upper and lower adjacent layers of the mining layer will diffuse through the surrounding rock to the mining surface, thereby increasing the gas emission from the working face. When the interval between the layers is the same, the higher the gas contents in the adjacent layer, the greater the gas emission from the working face.

(2) The depth of burial of coal seams

There is an important link between the depth of burial for coal seams and the gas content of coal seams, so it will also affect the amount of gas emitted from the working face. Under the ground, the deeper the burial depth of the coal seam, the correspondingly higher the gas pressure in the coal seam, which leads to an increase in the amount of gas absorbed by the coal body（Ji Zhenguang,2011）. According to scholars' research, within a certain range of buried depth, there is a linearly related law between the gas content and depth of the coal seam. In particular, due to the deep mining face, the growth rate of gas emission from the adjacent layer is even higher than that of the production layer, so the burial depth of the extracted coal seam is an important factor affecting the gas emission of the fully mechanized face.

(3) Mining seam inclination

Mining coal seam inclination will also affect the gas emission from the working face. According to the research, the law of gas flow in coal is that the flow of gas along the coal bed is completely easy to flow along the vertical plane, so the smaller the coal bed inclination is, the more favorable the coal gas storage. Because the gas permeability of the coal seam is stronger than the permeability of the surrounding rock, when the roof rock of the coal seam is well sealed, the smaller the coal bed inclination is, the greater the amount of gas stored in the coal body will directly lead to the higher gas content in the coal seam and further affect the gas emission from working face (Li Yukui, 2015) .

(4) Mining Coal Thickness

The thickness of the exploited coal seam mainly affects the gas emission from the coal face and from the falling coal. In general, if the thicker coal seam is to be mined, the area of the exposed coal wall in front of the working face will be larger after the coal cutter cuts coal, so the larger the gas emission from the coal wall is. In addition, the thicker the coal seam, the correspondingly larger mining thickness, the greater the amount of coal falling per unit of time, and the corresponding increase in gas emission from the falling coal.

(5) The adjacent coal seam thickness of mining working face

One of the sources of gas emission from the working face is the gas emission from the adjacent layer. According to the theory of the sub-source prediction method, the amount of gas emission near the coal seam in the coal mining face can be calculated according to formula (3.3):

$$q_L = \sum_{i=1}^{n} \frac{m_i}{M} k_i \cdot X_{0i} \tag{3.3}$$

m_i—The thickness of the i-th adjacent layer of the working face, m;

M—Working face mining thickness, m;

n—Number of mining face adjacent layers;

X_{0i}—Raw gas content of the i-th adjacent layer on the working face, m^3/t;

k_i—The gas emission rate of the i-th adjacent coal seam in the mining face, %, ki can be calculated according to formula (3.4):

$$k_i = 1 - h_i/h_p \tag{3.4}$$

h_i—the distance between the mining layer and the i-th adjacent layer, m;;

h_p—the scope of destruction of the surrounding rock of the production zone caused by the influence of mining activity. Within this range, the gas in adjacent layers can penetrate the working face through the destructed rock, m;

Based on the above two-step analysis, the thickness of the adjacent layer is an important factor affecting the gas emission from the working face. When the other conditions are constant, the gas emission amount and the thickness of the adjacent layer for a specific adjacent layer of the mining face are determined which has a positive relationship.

(6) Spacing between mining layer and adjacent layer in working face

Layer spacing between the production layer and adjacent layers also has an effect on the gas emission from the working face. In general, if the interval between layers is larger, the impact on the adjacent layer after the mining of the working face is relatively small, so the degree of expansion deformation of the adjacent layer is also relatively small, the gas emission from the adjacent layer to the working face is smaller, That is, the portion of the gas emission from the adjacent layer is relatively small. According to studies by scholars at home and abroad, there is an influential law shown in Figure 8 between the layer spacing of the mining layer in the working face and the gas emission rate in the adjacent layer.

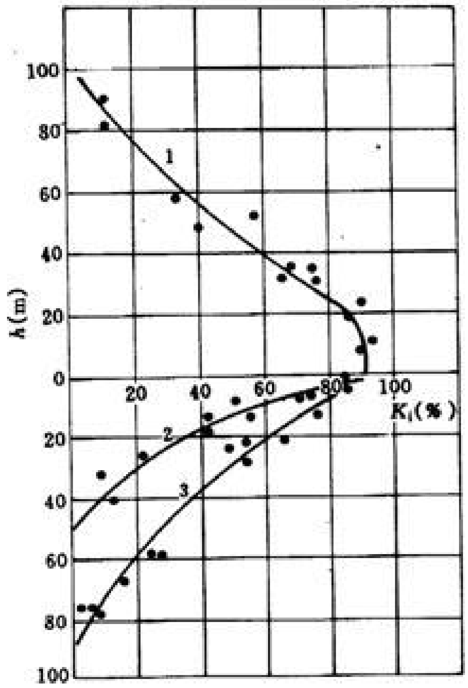


Figure 8 Relationship between gas emission rate and layer spacing in adjacent floors
1-Upper adjacent layer;2- Slowly inclined adjacent layer;3- Inclined or steeply inclined lower adjacent layer

3.2.2 Mining factors

(1) The roof management method of the goaf in the working face

Different methods of roof treatment in goafs have different effects on gas emission from the goaf. The commonly used roof management method in general coal mines is the whole slumping method. This kind of processing method has low economic cost, but it will have an important impact on the terrain of the mining area. After the roof is treated by the slumping method, the roof of the goaf is often broken and collapsed in a large area, and the “three belts” of the gob area are formed, which makes the gas in the upper adjacent layer fully depressurized and outflow the goafs, the gas in the goafs increases dramatically, further spreading the work surface. It can be seen from this that all Slump Laws have a great influence on the mining of adjacent layers of the working face. Some coal mines will use the full filling method or partial filling method to deal with goafs. For example, the Kailuan Group Tangshan Mine is located in the urban area. To prevent ground subsidence caused by mining, the rock fall is used to fully fill the goaf area of the working face, avoiding large areas of roof collapse. Obviously, the filling method to deal with goafs can better protect the roof, so that the impact on the adjacent layer of the working face is relatively small. Compared with the Slump method, the amount of gas emission from the working face is even smaller. In addition, there is a more common roof management method is coal pillar support method, that is, by leaving a certain pillar to prevent the roof from falling, the coal pillar method can also prevent the collapse of the roof in the gob area, fully reduce the influence of the mining layer, it can also reduce the amount of gas emission from the working face.

(2) Working face recovery rate

For a fully mechanized coal mining face, the planned coal mining capacity is fixed, and mining will inevitably lose a part of the coal due to various conditions during the mining process. This part of the coal loss includes the coal left behind during transportation, the coal that was not removed during the coal cutting process and the temporarily set coal column loss. A large part of the gas emission from the goaf is derived from these lost coal, and the recovery rate is used to reflect the ratio of the actual recovery of the working face to the recoverable amount. It can be seen that the lower the recovery rate, the more coal will be lost in the goaf during mining, and the higher the amount of gas emission from the lost coal will be, resulting in a continuous increase in the amount of goaf gas emission, when the gas pressure in the goaf is higher than the wind pressure in the working face, it will flock to the working face and affect the gas emission volume at the working face.

(3) Working face productivity

According to the provisions of the national coal mine safety regulations, the output design of the working face is limited by the gas emission requirement and cannot be set too large. According to the analysis of the source of gas emission from the working face, the gas emission from coal mining is an important source of gas emission from the working face. When the output of the working face is increased, it means that the amount of coal that was taken out of the working face per unit time increases, which will inevitably lead to an increase in the amount of gas released from coal falling per unit of time. As a result, the gas emission from the working face will increase. Therefore, the output of the working face is one of the important factors influencing the gas emission.

3.2.3 Production process factors

(1) Working face length

The length of the working face here refers to the length of the working face, which is the length of the walking distance when the shearer cuts a knife. The length of the working face determines the size of the exposed area of the coal wall after mining, and is also one of the determinants of the mining intensity of the working face. . When the thickness of the coal seam is fixed, the longer the working face, the larger the area of the exposed coal wall in front of the shearer will be, so the larger the gas emission from the coal wall will be, which will affect the amount of gas emission from the working face.

(2) Advance speed of working face

The speed of advancement of the working face is determined by the number of infeeds per day of the shearer, which in fact determines the amount of coal falling per unit time in the working face. The speed of advancement must also be limited by the gas concentration requirement, cannot be too fast. The speed of advancement of the working face mainly affects the amount of coal gas emitted from the working face.

(3) Air volume of the working face

The amount of air supply at the work surface also affects the amount of gas emitted. Under normal circumstances, the air supply to the working face is fixed. The wind pressure corresponding to the air volume tends to balance with the gas pressure at the working face and the goaf, which effectively suppresses the gas emission, so tthe gas emission and gas concentration under a fixed air volume will be in a relatively stable state. Once the air volume changes, this balance will be broken, resulting in disordered gas emission and gas concentration, and changes in the supply air volume will inevitably cause leakage. It has further caused changes in the concentration of air leakage gas (Wang Hongwu, 2017). For a working face with a drawout type mine ventilation system, the increase of air volume at the working face will increase the wind pressure in the working face area, but the wind pressure is negative pressure, so that the relationship between the gas pressure and the wind pressure balance is unbalanced, which inevitably leads to face the sharp increase in the amount of gushing and will also increase the amount of air leakage in the goaf, which will take away some of the gas from the goaf, causing the concentration of the gas in return airway to rise. After such a period of time, until the wind pressure is balanced after the gas pressure and air volume change on the work surface, the gas emission volume and gas concentration will gradually approach the original state. If the air volume is reduced, the regularity of gas emission changes is exactly the opposite of the above process. The duration of the change in gas emission caused by changes in the amount of wind may vary from a few minutes to several days, and is not fixed. In this process, the gas emission may also be multiple times than before.

(4) Working face gas drainage volume

Gas drainage can fundamentally effectively reduce the amount of gas emitted from the working face, which is one of the most commonly used gas control measures in coal mines. Gas drainage at working face includes gas pre-drawing in mining layer and gas drainage in goaf. Through the pre-extraction of gas from the working face, the gas in the coal body can be fully depressurized, which can effectively reduce the gas content in the coal seam, simultaneously reduce the gas pressure in the coal seam, greatly reduce the gas emission from the working face, and prevent coal and gas outburst. The gas drainage in the goaf area can effectively reduce the gas pressure in the goaf area, thereby reducing the amount of gas diffusion from the goaf to the working surface and reducing the amount of gas emission from the working face.

3.2.4 Natural factors

(1) Atmospheric pressure

Changes in atmospheric pressure have a significant effect on the amount of gas emitted from mines. In the draw-out type mine ventilation system, when the atmospheric pressure is reduced, the pressure of the ventilated roadway is also reduced, which results in an acceleration of the gas outflow rate and an increase in gas emission(Pa Shusen,et al,2014). Therefore, when the atmospheric pressure on the local area fluctuates significantly, we must pay special attention to changes in the amount of gas emissions, and take good preventive and control measures to prevent gas accumulation from causing accidents.

(2) Earthquakes

The impact of the earthquake on the gas emission from the working face is mainly reflected in the destruction of the geological structure of the coal mine during the earthquake, as well as the damage to underground gas prevention facilities and ventilation structures (Gao Haiying, 2017). Even a slight earthquake will cause damage to the working face coal seam and surrounding rock, break the original gas balance, increase the cracks in the coal and rock layers, and form a gas flow passage, which will increase the amount of gas emission in the adjacent layer. In addition, the earthquake may also cause closed goafs, damage to the protective coal pillars, and the proliferation of gas from adjacent goafs to mining face and goafs, which may also increase the amount of gas emission from the working face. In spite of an important influencing factor of gas emission during an earthquake, the probability of a typical earthquake occurring in a mining area is extremely small, and it is difficult to collect relevant data. This paper predicts the gas emission volume at the working face based on the neural network, taking into account the actual situation of the mine, and the prediction. The impact of the earthquake is not considered during the analysis.

3.2.5 Establishment of impact index system of methane emission quantity in fully mechanized mining face

According to the above theoretical analysis of the factors affecting the gas emission from fully mechanized coal mining face, the data required for the prediction of the neural network should be easily collected and extracted, and the data indicators of the factors affecting the gas outflow as shown in Figure 9 are preliminarily established.

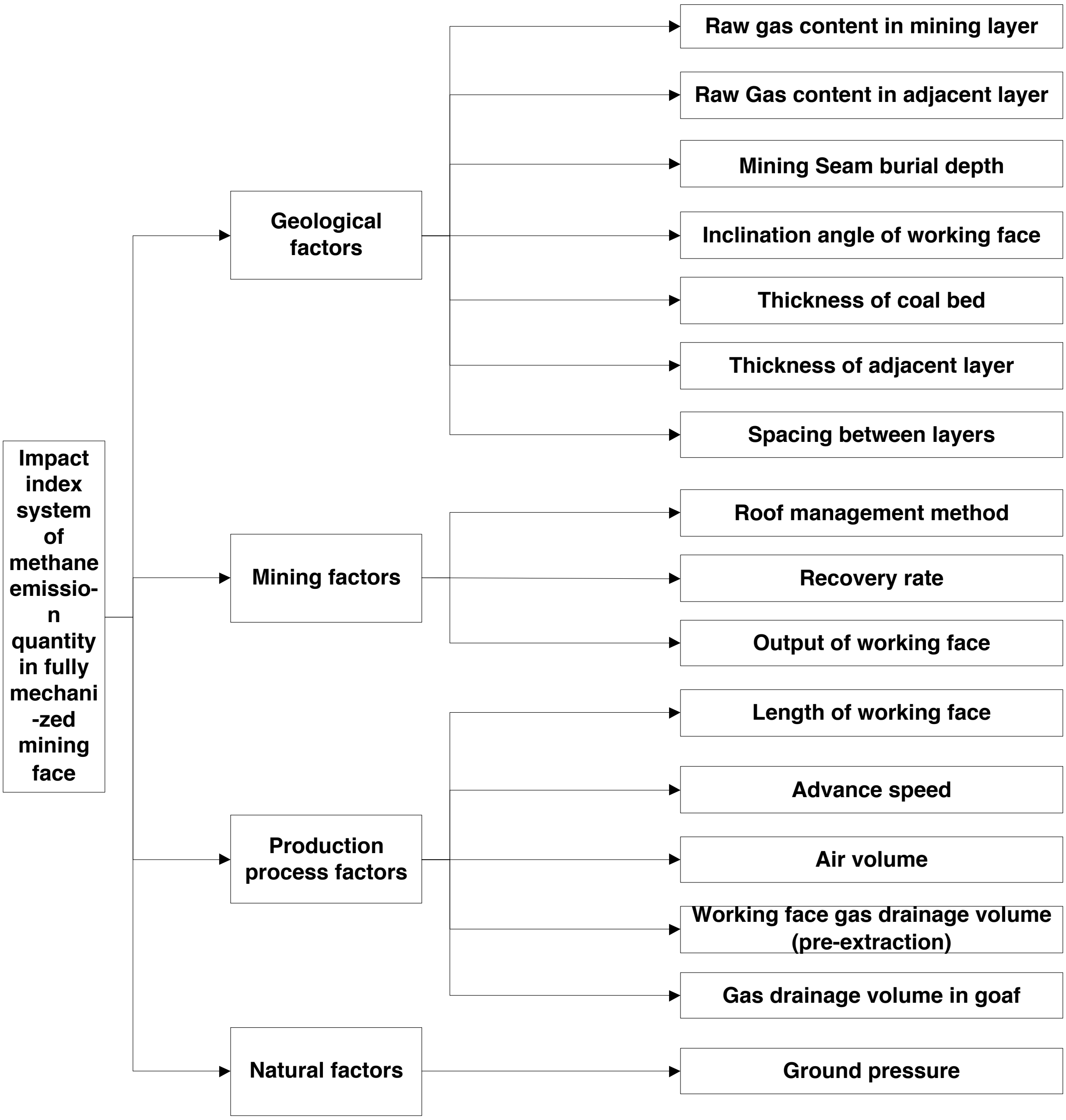


Figure 9 Data index system of inluencing factors of gas emission

The indicator system is divided into 4 secondary indicators and 16 tertiary indicators according to the factors affecting the gas emission from the fully mechanized coal mining face. Each index is a quantifiable indicator. The following indicators will be used as the basis for the index data.

4 Data analysis of Baode coal mine

This paper takes the 81505 fully mechanized mining face of Baode Coal Mine in Shendong Mining Area of Shenhua Group as the research object, and establishes the prediction model of BP neural network for gas emission in working face. For the gas emission prediction model, the historical data of the indicators listed in Figure 9 of the work face that is adjacent to the 81505 mining face of Baode Mine was taken as a sample to carry out the training and learning of the model. Finally, the geological and natural features, the production process and other parameters of the 81505 mining face are used to predict the gas emission from the working face. Therefore, the data collection process will be based on the indicators listed in Figure 9.

4.1 Brief introduction of Baode coal mine

(1) Occurrence of coal seam

The overall occurrence of the Baode ore formation is 350°, with a tendency of 260° and an inclination of 3-9°, usually about 5°. The elevation of the surface is +812.2 to +1148.1m, and the maximum height difference is 335.9m. The recoverable coal seams are the No. 8 coal seam of the Permian Shanxi Formation and the 10#, 11# and 13# coal seams of the Taiyuan Formation in the Carboniferous system. The thickness and interval thickness of the coal seams from the top to the bottom are: the thickness of the 8# coal seam is 2.16. ~10.29 m, the average coal thickness is 6.84 m, and the interval between the layers of the 10th coal seam is 29 m; the thickness of the 10 # coal seam is 1.25 to 1.90 m, the average coal thickness is 1.51 m, and the interlayer spacing with the 11# coal seam is 5.51 m The thickness of the 11# coal seam is 1.12-13.27 m, the average coal thickness is 7.15 m, and the interlayer spacing with the 13 # coal seam is 23.86 m; the thickness of the 13 # coal seam is 0-11.24 m, and the average coal thickness is 3.67 m. Among them, the 8#, 10#, and 11# coal seams can be mined in the entire area, and the 13# coal seam can only be partially mined.

(2) Occurrence of 8# coal seam

The working face of this study is to mine the coal seam in No. 8 and the collected data comes from this coal seam. Therefore, the 8# coal seam is separately described in details here. The depth of 8# coal seam mining is +940 ~ +420 m, and the depth of burial is 122 ~ 663 m. The average dip angle of the 8# coal seam is 3.5°, and the coal seam thickness is about 6.8 m. and basically thick coal seam or extra thick coal seam. The 8# coal seam contains 1 to 8 layers of magma, the thickness of the magmatic layer is about 1.06 m, and the lithology is mainly mudstone and carbonaceous mudstone.

It was determined that the variation law of the gas content in coal seam 8# was W=-0.0239H+20.8112, and the gradient of gas content was 2.73 $m^3/t \cdot 100m$. Gas pressure P=-0.005H+4.570 MPa, gas pressure gradient is 0.50 Mpa/100m. The depth of the deep boundary of minefield 8# is +500 m, and the gas content is about 8.73 m^3/t. The permeability coefficient of coal seam 8# is 0.17-0.8 $m^2/（MPa^2 \cdot d）$, and the attenuation coefficient of gas flow from drill holes is 0.131～0.0356 d^{-1}, which is a drawable coal seam. In 2014, mine gas classification was identified as absolute discharge of 130.96 m3/min and relative emission of 9.73 m^3/t, belonging to high gas mines.

(3) Production System Overview

The mining mode of Baode Coal Mine is the comprehensive pioneering mode of "adit+ inclined shaft + vertical shaft". Mining elevation +940 ~ +420m, mining level is +684 m. The 8# coal seam of Baode Coal Mine in Kangsun Road (horizontal lanes with elevations of +720 to +760 m), main and auxiliary roads of No. 8 coal seam, main and auxiliary transportation lanes of Wupan District, divides the minefield into four panels, which are the first, second, third and fifth panels. The number of planned mining faces is 49. Now 28 of them have been taken and one is being mined.

(4) Overview of 81505 working face

The 81505 face is at the lower part of the 81504 working face that has been mined, with an average distance of 51 m. 81505 working face mining distance is 2090m, working face length of 240m, coal geological reserves of 571.5 million tons, mining of 5.315 million tons of coal. The coal seam floor height of the working face is +649～684 m, the maximum relative height difference is 35 m, the coal bed inclination angle is 5～9°, and the average is 7°. The coal seam is oriented to the north and south. The thickness of the coal seam is between 6.6 and 8.2 m, with an average of 7.4 m. The coal seam structure is complex. The average number of the coal seam with dirt band is 3 to 4 layers, and the maximum thickness of the single layer is 0.60 m, and the average thickness of pure coal is 6.6 m.

The 81505 working face adopts a two-entering and two-return "U" type ventilation method. The 81505 working face coal gas content is 4.38 m^3/t. It is expected that the absolute gas emission from the working face during mining will be 19.6 m^3/min, of which the extraction volume in the gob is about 10.5 m^3/min, the pre-pumping volume of the coal bed is about 4.1 m^3/min, and the air displacement is about 5 m^3/min.

4.2 Methane Emission related data collection

Baode Mine used 8# coal seam as the first mining coal seam. The coal seam was divided into 5 panels and 49 working faces. The 81101 working face was firstly mined in 2003. In 2017, the recovery work of 81504 working face was completed and the 81505 working face was continued to be mined. The 8# coal seam currently completed a total of 28 working faces. The lower adjacent layer of the 8# coal seam is 10# coal seam with an average spacing of 29 m. The Baode Mine belongs to the high gas mine and the gas drainage system is installed on the working face. In order to predict the amount of gas emission from the newly mined 81505 working face through the BP neural network model, the 16 influencing factors of the gas emission identified in Figure 3.2 are used as data collection targets and a network training sample was created using the data of the 28 working faces that have been collected from the 8# coal seam.

The following difficulties are encountered in the process of data collection for the indicators of the factors affecting gas emission: First, some indicator data are not monitored, and they need to be extracted from relevant documents and drawings of the working face of the mine, and some of the data also concern confidentiality, which can not be copied out, and finally we can only get to the consultation, consulting production staff to solve. Secondly, due to the relatively long time span of mining and the large number of impact indicators, and also computer technology was not popular enough in the early years. Therefore, the data of certain indicators may not be directly available. After consultation with the staff of the production technology department, we go and find by ourselves. In addition, the data of some indicators are dynamically changing in the process of mining. After consultation with on-site staff to fully understand the actual production situation, select representative data.

After the field survey of Baode Mine, finally through the collection, collation the author obtained data samples as shown in Table 1 and Table 2. Among them, the index of the roof management method belongs to the classification index and uses numbers to represent different types. In this paper, 1 represents all the collapses, 2 represents the filling method, and 3 represents the pillar support method.

Working face number	Raw gas content in mining layer （m^3/t）	Mining Seam burial depth (m)	Thickness of coal bed(m)	Inclination angle(°)	Length of woking face	Advance speed （m/d）	Recovery rate	Gas content in adjacent layer （m^3/t）	Thickness of adjacent layer(m)
81101	3.98	248	5.9	7	205	3.30	0.903	4.02	2.11
81201	4.14	260	6.4	8	240	3.20	0.910	3.64	1.72
81110	4.58	282	5.8	7	240	3.38	0.882	4.34	1.48
81109	4.40	256	5.6	6	240	3.30	0.892	4.55	1.65
81202	4.22	246	6.3	7	240	3.45	0.873	3.71	1.72
81303	4.80	340	6.8	9	300	3.55	0.860	4.81	1.93
81501	4.61	290	7.1	7	240	3.50	0.880	4.52	1.65
81306	4.68	293	7.1	8	260	3.53	0.875	4.60	1.86
81112	4.21	323	6.9	8	315	3.50	0.876	4.04	2.18
81107	4.03	254	6.4	6	240	3.40	0.900	4.25	1.69
81106	4.34	267	6.5	6	240	3.45	0.912	4.02	1.74
81104	4.38	254	6.1	8	200	3.25	0.928	3.98	1.58
81305	4.67	280	6.8	8	240	3.45	0.890	3.56	2.02
81301	4.43	250	6.6	5	240	4.32	0.872	4.20	1.78
81302	4.16	274	6.7	6	240	3.40	0.868	4.79	1.82
81304	4.62	289	6.8	7	265	3.50	0.892	3.85	1.81
81108	4.24	255	6.2	7	240	3.28	0.900	3.64	1.72
81102	4.67	263	6.5	6	240	3.30	0.905	3.84	1.91
81502	4.60	314	7.2	8	240	3.53	0.920	4.56	1.58
81111	4.78	277	6.9	10	300	3.81	0.902	4.95	1.89
81504	4.21	258	6.4	9	240	3.17	0.880	3.56	1.74
81503	4.71	270	6.9	8	240	3.57	0.869	3.79	1.77
81103	3.83	264	6.5	6	215	3.08	0.920	3.11	1.78
81203	3.34	257	6.6	7	200	3.32	0.923	3.76	1.62
81300-2	4.45	244	7.3	7	240	3.40	0.910	4.01	1.98

81300-1	4.67	260	7.6	10	240	3.32	0.870	4.59	1.89
81504	4.53	260	6.6	9	240	3.42	0.890	3.82	1.71
81100	5.56	281	6.9	9	300	3.40	0.873	4.82	1.97

Table 1 Working face gas emission impact indicator data (1)

Working face number	Spacing between layer(m)	Roof management method	Output of workng face （t/d）	Gas drainage in goaf （m^3/min）	working face gas drainage volume (pre-extraction) （m^3/min）	Air volume （m^3/min）	Ground pressure(Pa)	Gas emission volume from working face （m^3/min）
81101	32.3	1	3225	9.3	5.3	2212	1019.2	4.34
81201	29.2	1	3451	9.7	4.9	2104	1017.2	4.45
81110	27.4	1	3478	10.6	5.5	2326	1016.8	4.72
81109	30.9	1	3104	9.8	5.4	3142	1012.6	4.57
81202	32.6	1	3242	9.6	5.1	2331	1010.0	4.49
81303	24.5	1	3679	10.3	4.3	3120	1009.0	5.20
81501	29.2	1	3475	10.3	4.8	2257	1009.8	4.87
81306	26.7	1	3410	10.2	3.9	2910	1009.8	5.06
81112	24.4	1	3139	10.9	3.4	3202	1007.1	5.24
81107	34.8	1	3354	10.2	4.2	2455	1019.5	4.60
81106	37.1	1	3387	10.3	3.9	2500	1019.5	4.68
81104	35.1	1	3120	9.3	5.4	2548	1019.6	4.21
81305	25.7	1	3412	10.8	4.5	2552	1019.6	4.95
81301	29.2	1	3396	10.3	3.5	2518	1018.0	4.65
81302	27.9	1	3407	10.6	3.3	2500	1017.9	4.92
81304	27.3	1	3456	10.9	3.5	2649	1019.5	5.04
81108	24.2	1	3335	9.3	5.3	2310	1019.7	4.57
81102	31.2	1	3420	9.7	4.7	2670	1020.2	4.78
81502	28.5	1	3478	10.9	4.5	2526	1020.2	4.95
81111	27.5	1	3340	11.5	3.5	2837	1011.6	5.16
81504	23.8	1	3345	9.7	4.3	2268	1026.6	4.48
81503	27.2	1	3467	10.6	4.3	2780	1012.5	5.03
81103	36.2	1	3170	11.3	5.4	2243	1026.5	3.88
81203	29.2	1	3112	9.4	5.3	2340	1030.7	3.78
81300-2	26.5	1	3496	10.5	3.5	2587	1026.2	4.59

81300-1	30.6	1	3507	10.8	4.8	2883	1025.9	5.18
81504	29.3	1	3450	10.2	4.6	2468	1022.9	4.78
81100	24.2	1	3442	11.4	3.4	3164	1014.9	5.36

Table 2 Working face gas emission impact indicator data (2)

4.3 Data feature analysis

When using the BP neural network to analyze the problem, it is required that the input component meets the output component to have a greater correlation. In the forecast model of gas emission from the fully mechanized coal mining face in this paper, the input component is the 16 impact indicators of gas emission from the working face, and the output is the gas emission from the working face. The third chapter of this paper has theoretically analyzed the influencing factors of gas emission from the working face. After obtaining the data sample, it is necessary to first use the data to analyze the correlation between the impact indicators and the gas emission volume at the working face. To verify the rationality of the indicators taken, but also reflects the scientific nature of this paper using the neural network model. This section will use the grey correlation analysis method to analyze the correlation between the impact indicators and the gas emission volume at the work surface.

4.3.1 Grey correlation analysis

The grey correlation analysis method is a mathematical method used for multi-factor statistical analysis. The calculation process is simple, rapid and widely used. For a sample composed of a number of variables and values, in order to study the tightness of the association between variables, the correlation degree can be used as a standard. The correlation between variables is calculated and sorted by size, so that the degree of association of variables can be clearly known. The calculated degree of correlation is a positive number within the interval [0,1], and the greater the degree of correlation, the more significant the relationship between variables. The advantage of the grey relational analysis method is that there is no need to consider the number of samples and the possible distribution rules of the sample itself. Starting from the data itself, especially when the sample data has a large gray scale, the grey correlation analysis method can be quickly explored to know how variables are closely related to important factors(Yan Aihua, 2010). The detailed calculation process of the grey correlation analysis method is generally divided into the following steps:

(1) Determine the analysis index system according to the purpose of the analysis and collect the analysis data.

Let n data sequences form the following matrix:

$$\left(X_1', X_2' \cdots, X_n'\right)=\begin{pmatrix} x_1'(1) & x_2'(1) & \cdots & x_n'(1) \\ x_1'(2) & x_2'(2) & \cdots & x_n'(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1'(m) & x_2'(m) & \cdots & x_n'(m) \end{pmatrix} \tag{4.1}$$

Where m is the number of indicators, $X_i'=\left(x_i'(1), x_i'(2), \cdots, x_i'(m)\right)^T$, $i=1,2,\cdots,n$.

(2) Determine the reference data column

The reference data column is an ideal comparison standard. The reference data column can be composed of the optimal value (or the worst value) of each indicator, and other reference values can also be selected according to the evaluation purpose, expressed as:

$$X_0'=\left(x_0'(1), x_0'(2), \cdots, x_0'(m)\right) \tag{4.2}$$

(3) Standardized processing of indicator data

When analyzing problems, there are often cases where the physical meanings of the factors are different. Therefore, the dimension of the data is also different. It is meaningless to compare the data directly. After dimensionless standardization, the data is in the same range, which is convenient. Comparisons make it easier to draw conclusions. Therefore, it is necessary to conduct dimensionless standardization before analysis. The commonly used dimensionless methods are the mean method (formula (4.3)) and the initial value method (formula (4.4)).

$$x_i(k)=\frac{x_i'(k)}{\frac{1}{m}\sum_{k=1}^{m} x_i'(k)} \tag{4.3}$$

$$x_i(k)=\frac{x_i'(k)}{x_i'(1)} \tag{4.4}$$

Where $i=0,1,\cdots,n$; $k=1,2,\cdots,m$.

The non-dimensionalized data sequence forms the following matrix:

$$\left(X_0, X_1, \cdots, X_n\right)=\begin{pmatrix} x_0(1) & x_1(1) & \cdots & x_n(1) \\ x_0(2) & x_1(2) & \cdots & x_n(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_0(m) & x_1(m) & \cdots & x_n(m) \end{pmatrix} \quad (4.5)$$

(4) Calculate the absolute difference between the corresponding elements of the comparison sequence and the reference sequence: $\left|x_0(k)-x_i(k)\right|$, k=1,2, …m, i=1, 2, …n.

(5) Determine $\min\limits_{i=1}^{n}\min\limits_{k=1}^{m}\left|x_0(k)-x_i(k)\right|$ and $\max\limits_{i=1}^{n}\max\limits_{k=1}^{m}\left|x_0(k)-x_i(k)\right|$.

(6) Calculate the correlation coefficient

Calculate the correlation coefficient $\zeta_i(k)$ for the corresponding elements of the comparison sequence and the reference sequence, and calculate the formula as follows:

$$\zeta_i(k)=\frac{\min\limits_{i}\min\limits_{k}\left|x_0(k)-x_i(k)\right|+\rho\cdot\max\limits_{i}\max\limits_{k}\left|x_0(k)-x_i(k)\right|}{\left|x_0(k)-x_i(k)\right|+\rho\cdot\max\limits_{i}\max\limits_{k}\left|x_0(k)-x_i(k)\right|} \quad (4.6)$$

In the formula, ρ is the resolution coefficient, and it is set in (0, 1). If the value of p is smaller, the difference between the correlation coefficients is larger, and the distinguishing ability is stronger, usually 0.5.

(7) Calculate the correlation order

Calculate the mean value of the correlation coefficient of each corresponding index of the comparison sequence and the reference sequence to reflect the correlation between each evaluation index and the reference sequence. The average value is the correlation order, and the expression is as follows:

$$r_{0i}=\frac{1}{m}\sum_{k=1}^{m}\zeta_i(k) \quad (4.7)$$

The degree of association between the indicators is mainly described by the order of the degree of association, not only the size of the association. The correlation order of the m subsequences to the same parent sequence is arranged in the order of magnitude, which forms the association order. The size of the relevance indicator reflects the degree of interaction between the two columns of data. The greater the degree of association, the greater the degree of mutual influence between the two factors. However, it does not mean whether the two factors are linear or other relationships.

4.3.2 Correlation analysis of impact index of gas emission quantity

According to the grey correlation analysis method introduced in the previous section, the gas emission from the Baode Mine and the correlations between the influencing factors are analyzed. Based on the data of the 28 mining face sheets collected in Table 1 and Table 2, Excel software was used for calculation. In order to facilitate the analysis, the indicators of each influencing factor are expressed in English codes, as shown in Table 3. The gas emission from the work surface is represented by Y. In the analysis process, 16 influencing factors are used as comparison sequences, and the gas emission from the working surface is taken as reference sequence.

Indicator	Raw gas content in mining layer	Burial depth of coal seam	Thickness of coal seam	Inclination angle	Length of working face	Advance speed	Recovery rate	Raw gas content in adjacent layer
code	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
indicator	Thickness of adjacent layer	Spacing between layers	Roof management method	Production of working face	Gas drainage wolume in goaf	Gas drainage volume in working face	Air volume	Ground pressure
code	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}

Table 3 The English code of each influencing factor indicator

The data was dimensionlessed using the mean method. The results are shown in Table 4 and Table 5.

Working face number	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
81101	0.8999	0.9126	0.8910	0.9378	0.8343	0.9617	1.0124	0.9760
81201	0.9360	0.9568	0.9666	1.0718	0.9767	0.9326	1.0202	0.8837
81110	1.0355	1.0377	0.8759	0.9378	0.9767	0.9850	0.9888	1.0537
81109	0.9948	0.9420	0.8457	0.8038	0.9767	0.9617	1.0000	1.1047

81202	0.9541	0.9052	0.9515	0.9378	0.9767	1.0054	0.9787	0.9007
81303	1.0853	1.2511	1.0270	1.2057	1.2209	1.0346	0.9642	1.1678
81501	1.0423	1.0672	1.0723	0.9378	0.9767	1.0200	0.9866	1.0974
81306	1.0581	1.0782	1.0723	1.0718	1.0581	1.0287	0.9810	1.1168
81112	0.9519	1.1886	1.0421	1.0718	1.2820	1.0200	0.9821	0.9808
81107	0.9112	0.9347	0.9666	0.8038	0.9767	0.9908	1.0090	1.0318
81106	0.9813	0.9825	0.9817	0.8038	0.9767	1.0054	1.0225	0.9760
81104	0.9903	0.9347	0.9213	1.0718	0.8140	0.9471	1.0404	0.9663
81305	1.0559	1.0304	1.0270	1.0718	0.9767	1.0054	0.9978	0.8643
81301	1.0016	0.9200	0.9968	0.6699	0.9767	1.2590	0.9776	1.0197
81302	0.9406	1.0083	1.0119	0.8038	0.9767	0.9908	0.9731	1.1629
81304	1.0446	1.0635	1.0270	0.9378	1.0785	1.0200	1.0000	0.9347
81108	0.9587	0.9384	0.9364	0.9378	0.9767	0.9559	1.0090	0.8837
81102	1.0559	0.9678	0.9817	0.8038	0.9767	0.9617	1.0146	0.9323
81502	1.0401	1.1555	1.0874	1.0718	0.9767	1.0287	1.0314	1.1071
81111	1.0807	1.0193	1.0421	1.3397	1.2209	1.1103	1.0113	1.2018
81504	0.9519	0.9494	0.9666	1.2057	0.9767	0.9238	0.9866	0.8643
81503	1.0649	0.9936	1.0421	1.0718	0.9767	1.0404	0.9743	0.9201
81103	0.8660	0.9715	0.9817	0.8038	0.8750	0.8976	1.0314	0.7551
81203	0.7552	0.9457	0.9968	0.9378	0.8140	0.9675	1.0348	0.9129
81300-2	1.0061	0.8979	1.1025	0.9378	0.9767	0.9908	1.0202	0.9736
81300-1	1.0559	0.9568	1.1478	1.3397	0.9767	0.9675	0.9754	1.1144
81504	1.0242	0.9568	0.9968	1.2057	0.9767	0.9967	0.9978	0.9274
81100	1.2571	1.0340	1.0421	1.2057	1.2209	0.9908	0.9787	1.1702
Working face number	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
81101	1.1746	1.1128	1.0000	0.9576	0.9029	1.1920	0.8554	1.0012
81201	0.9575	1.0060	1.0000	1.0247	0.9417	1.1020	0.8137	0.9992
81110	0.8239	0.9440	1.0000	1.0327	1.0291	1.2369	0.8995	0.9989
81109	0.9185	1.0646	1.0000	0.9217	0.9515	1.2145	1.2151	0.9947
81202	0.9575	1.1232	1.0000	0.9627	0.9320	1.1470	0.9015	0.9922
81303	1.0744	0.8441	1.0000	1.0924	1.0000	0.9671	1.2066	0.9912
81501	0.9185	1.0060	1.0000	1.0318	1.0000	1.0795	0.8728	0.9920
81306	1.0354	0.9199	1.0000	1.0125	0.9903	0.8771	1.1254	0.9920
81112	1.2135	0.8407	1.0000	0.9321	1.0583	0.7647	1.2383	0.9893

81107	0.9408	1.1990	1.0000	0.9959	0.9903	0.9446	0.9494	1.0015
81106	0.9686	1.2782	1.0000	1.0057	1.0000	0.8771	0.9668	1.0015
81104	0.8795	1.2093	1.0000	0.9264	0.9029	1.2145	0.9854	1.0016
81305	1.1245	0.8854	1.0000	1.0131	1.0485	1.0120	0.9869	1.0016
81301	0.9909	1.0060	1.0000	1.0084	1.0000	0.7871	0.9738	1.0000
81302	1.0131	0.9612	1.0000	1.0117	1.0291	0.7422	0.9668	0.9999
81304	1.0076	0.9406	1.0000	1.0262	1.0583	0.7871	1.0244	1.0015
81108	0.9575	0.8338	1.0000	0.9903	0.9029	1.1920	0.8933	1.0017
81102	1.0632	1.0749	1.0000	1.0155	0.9417	1.0570	1.0326	1.0022
81502	0.8795	0.9819	1.0000	1.0327	1.0583	1.0120	0.9769	1.0022
81111	1.0521	0.9475	1.0000	0.9918	1.1165	0.7871	1.0972	0.9937
81504	0.9686	0.8200	1.0000	0.9932	0.9417	0.9671	0.8771	1.0085
81503	0.9853	0.9371	1.0000	1.0295	1.0291	0.9671	1.0751	0.9946
81103	0.9909	1.2472	1.0000	0.9413	1.0971	1.2145	0.8674	1.0084
81203	0.9018	1.0060	1.0000	0.9241	0.9126	1.1920	0.9049	1.0125
81300-2	1.1022	0.9130	1.0000	1.0381	1.0194	0.7871	1.0005	1.0081
81300-1	1.0521	1.0543	1.0000	1.0413	1.0485	1.0795	1.1149	1.0078
81504	0.9519	1.0095	1.0000	1.0244	0.9903	1.0345	0.9544	1.0048
81100	1.0966	0.8338	1.0000	1.0220	1.1068	0.7647	1.2236	0.9970

Table 4 The result of dimensionless processing of comparison sequence

Working face number	Y	Working face number	Y	Working face number	Y	Working face number	Y
81101	0.9127	81306	1.0641	81302	1.0346	81503	1.0578
81201	0.9358	81112	1.1019	81304	1.0599	81103	0.8790
81110	0.9926	81107	0.9673	81108	0.9610	81203	0.8622
81109	0.9610	81106	0.9842	81102	1.0052	81300-2	0.9652
81202	0.9442	81104	0.8853	81502	1.0409	81300-1	1.0893
81303	1.0935	81305	1.0409	81111	1.0851	81504	1.0052

81501	1.0241	81301	0.9778	81504	0.94 21	81100	1.1271

Table 5 The result of dimensionless processing of reference sequence

After obtaining the absolute difference between the corresponding elements of the comparison sequence and the reference sequence, the maximum absolute difference Max=0.3682 and the minimum absolute difference Min=0.0001 are obtained. Then according to equation (4.6) and equation (4.7) to obtain the order of Y and Xi, the results shown in Table 6, in order to more intuitive analysis of the results, corresponding results of the histogram, see Figure 10.

Correlation order	Raw gas content in mining layer	Burial depth of coal seam	Thickness of coal seam	Inclination angle	Length of working face	Advance speed	Recovery rate	Raw gas content in adjacent layer
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Gas emission quantity:Y	0.8767	0.8250	0.8401	0.6909	0.8289	0.8451	0.7779	0.7479
Correlation order	Thickness of adjacent layer	Spacing between layers	Roof management method	Production of working face	Gas drainage wolume in goaf	Gas drainage volume in working face	Air wolume	Ground pressure
	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
Gas emission quantity:Y	0.8039	0.6425	0.7989	0.8409	0.8758	0.5986	0.7889	0.7945

Table 6 Correlation order between Y and X

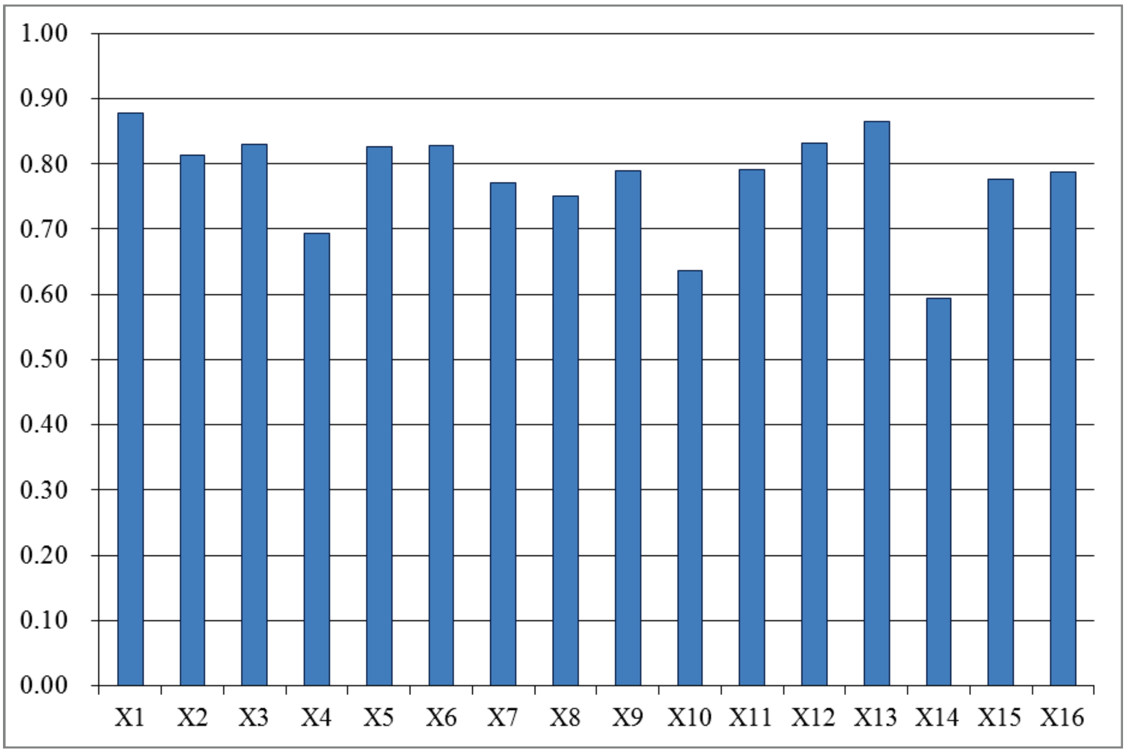


Figure 10 The histogram of the correlation order of each factor

Analysis of Table 6 and Figure 10 can be obtained through the analysis of the grey correlation degree. The correlation degree of the sixteen influencing factor indicators obtained from the theoretical analysis of the gas emission from the working face is relatively high, basically all above 0.6, indicating that the second chapter The theoretical analysis determines the influence index of gas emission from the working face is reasonable, and it also shows that the use of BP neural network to predict the amount of gas emission from the working face is in line with the requirements and is scientific. The impact indicators with the highest correlation with the gas emission from the working face are the raw gas content of the production layer, the gas drainage volume of the goaf area, the output of the working face, the depth of the coal seam, the length of the working face, the advancing speed of the working face, and the thickness of the coal seam. The correlation of the seven impact indicators are all above 0.8, followed by the roof management method, adjacent layer thickness, ground pressure, working surface air volume, working face recovery rate, the raw gas content of adjacent layers, coal seam inclination, and gas drainage volume (pre-extraction) and spacing between layers, which indicate that the gas content in the mining layer and the output of the working face are the decisive factors for the gas emission from the working face. This is basically in line with the theoretical conclusions of the scholars on gas emission.

5 BP neural network prediction of gas emission

There are many influencing factors of gas emission from fully mechanized coal mining face, and the prediction of gas emission from working face can provide decision-making basis for mine gas prevention and control work, which is of great significance to coal mine safety management. The BP neural network has a strong ability to deal with nonlinear problems. Through the amount of gas emission and its influencing factors at the fully mechanized coal mining face, a BP neural network model is established. Through training model by the sample data, the law of internal influence between the amount of gas emission and its influencing factors are learned. Finally, use the optimal model of training to predict the gas emission from the working face under other geological conditions.

5.1 BP Neural Network Prediction Process for Gas Emission Quantity at Fully Mechanized Face

According to the foregoing discussion, it is feasible that the BP neural network is used to predict the gas emission in fully mechanized coal mining face. The entire predicting process is roughly as shown in the figure below.

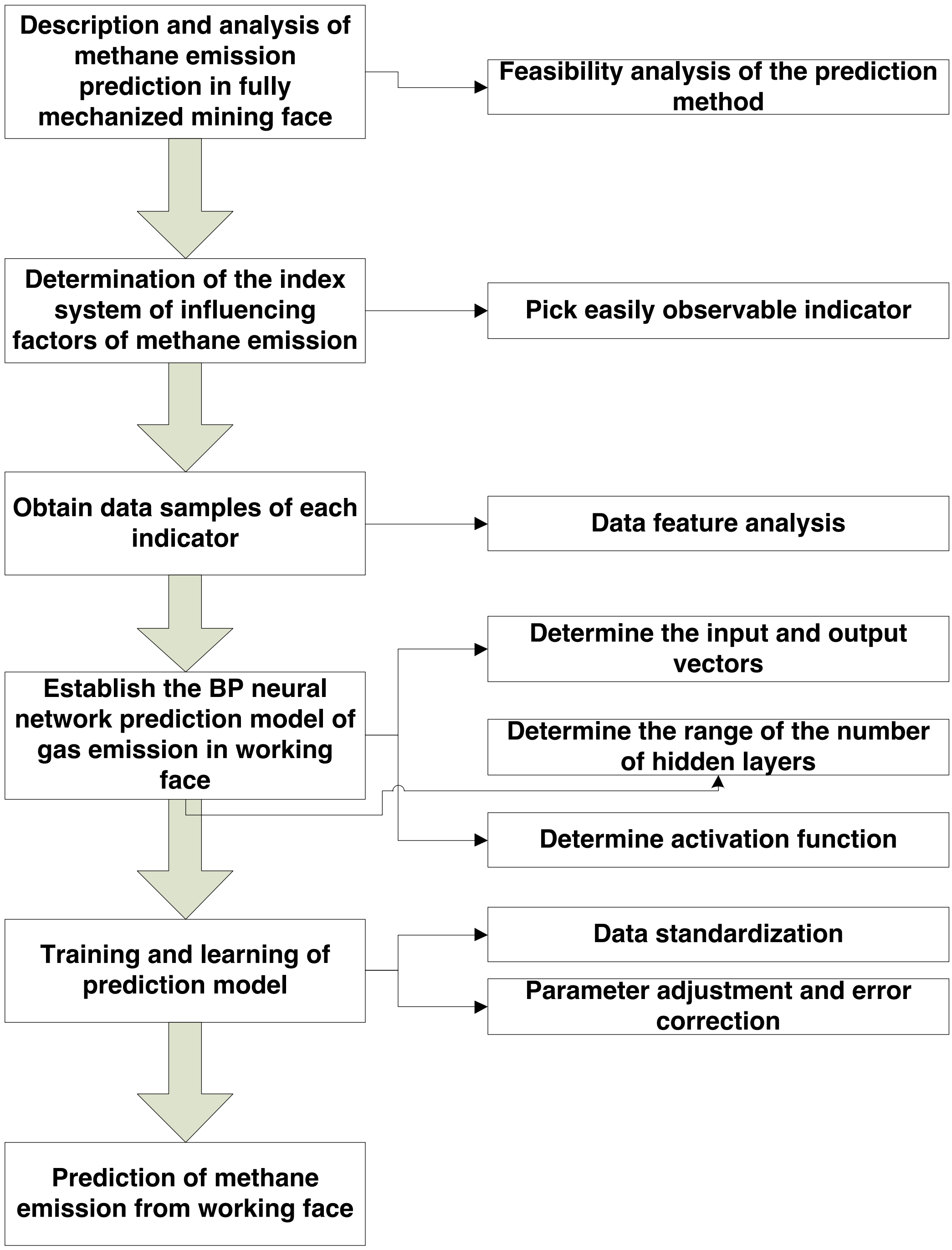


Figure 11 The flowchart of BP neural network forcasting gas emission at fully mechanized face

5.2 Establishment of BP Neural Network Prediction Model for gas emission quantity at fully mechanized mining face

5.2.1 Introduction of MATLAB platform

MATLAB 2014a is a commercial mathematics software developed by The MathWorks in the United States, providing users with a visual operating platform and interactive environment. MATLAB 2014a mainly includes MATLAB and Simulink. Its functions include the development of new algorithms, visualization of data processing, numerical simulation, system simulation, data analysis, mathematical modeling, matrix operations, etc., and it is an international absolute leader in the ranks of scientific computing software. Currently, it is widely used in many fields of scientific research and engineering design.

Neural network is a functional module in MATLAB software. In MATLAB, there is both a neural network module toolbox and a neural network algorithm. The BP neural network model of the gas emission quantity at the fully mechanized coal mining face of this paper will be implemented by programming on the MATLAB 2014a software platform. By invoking specific functions on neural network in MATLAB, establishing a predictive model, importing sample data, and issuing training and learning instructions to the model, comparing the errors of each training result, determining the optimal predictive model, and finally obtaining the predicted result.

5.2.2 Prediction model input vector and output vector determination

The single hidden layer network structure of the BP neural network model for the gas emission quantity at the fully mechanized coal mining face, according to the analysis above, has a high correlation between the selected impact indicators and the gas emission volume at the working face, so 16 impact indicators are used as the the input vector of the network. The number of input layer nodes is 16, which are the raw gas content of the mining layer, the depth of the coal seam, the thickness of the coal seam, the inclination angle of the coal seam, the length of the working surface, the advancing speed of the working face, the recovery rate of the working face, the raw gas content of the adjacent layer, adjacent layer thickness, layer spacing, roof management method, output of working face, gas drainage volume in goaf, gas drainage volume at working face, air volume at work surface, atmospheric pressure at ground, set gas emission quantity at working face as output vector, generally three-layer network structure of the single using S-type activation function can usually approximate any nonlinear function, so this paper uses a single hidden layer network structure (Liang Huazhen, et al,2007). The network structure is shown in Figure 12.

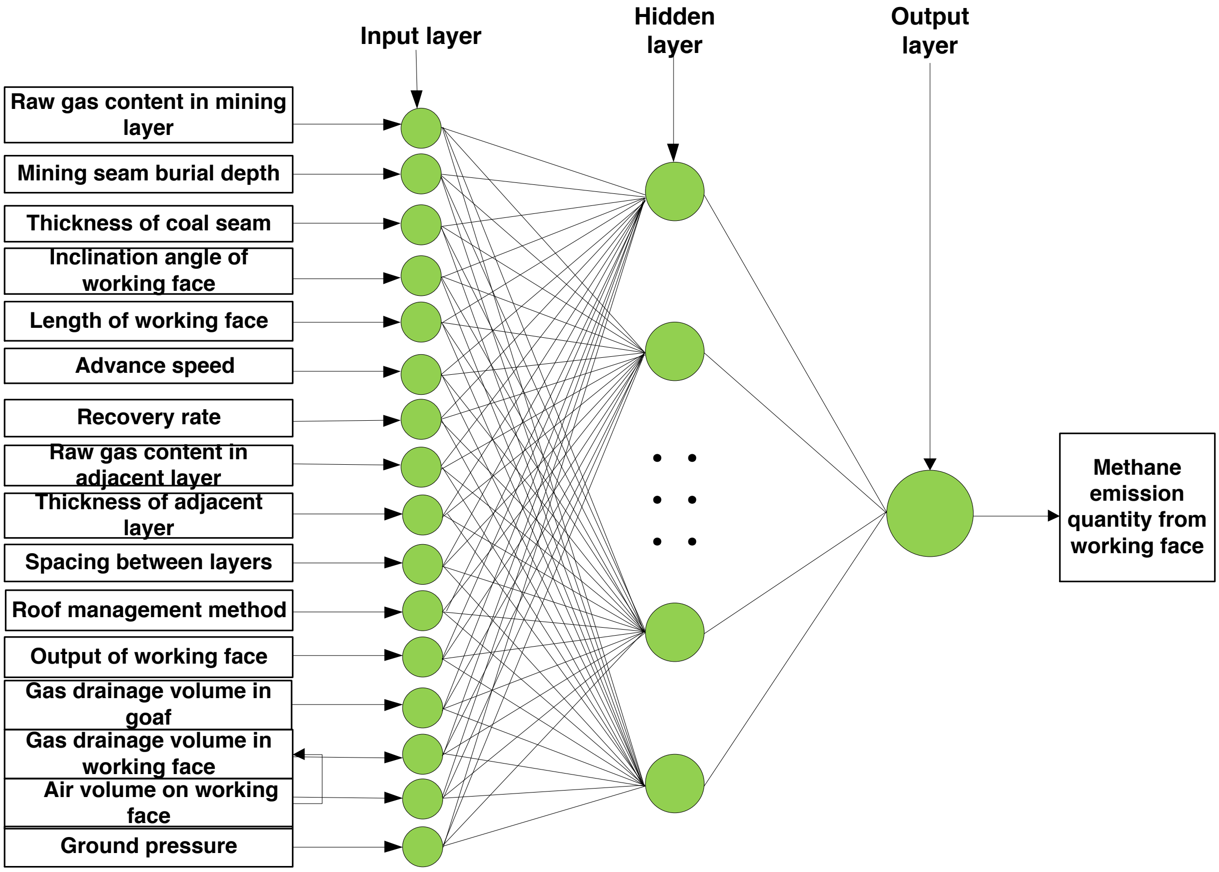


Figure 12 Neural network structure of gas emission quantity prediction in fully mechanized face

5.2.3 Determination of other structural parameters of the prediction model

(1) Determination of the number of hidden layer nodes

The number of hidden layer nodes has an important influence on the performance of the neural network. If the number of nodes is too large, the entire network will be more complicated and the operation time will be longer. If the number of nodes is too small, the network learning ability will be poor and the error will be large. Therefore, choosing the number of hidden layer nodes is a crucial step in the process of neural network solving problems. This paper first determines the number of hidden layer nodes of the prediction model based on empirical formulas as [6,16], and the final number of nodes will be determined through experiments in the training process.

(2) Determination of activation function

The input vector and output vector of the BP neural network prediction model of gas emission quantity are both positive, so the prediction model adopts logsig type activation function.

5.3 BP neural network prediction model training for gas emission quantity of fully mechanized coal mining face

5.3.1 Determination of training parameters

(1) Determination of training parameters

During the training process, the maximum number of training steps epochs=500, the training target minimum error goal=0.01, the learning rate lr=0.01, the interval step number of each training result show=50, and the momentum factor mc=0.9.

(2) Determination of training function

The training function uses the trainlm function, which corresponds to the Levenberg-Marquardt algorithm, which uses the gradient to find the minimum (large) value. It is the most widely used nonlinear least-squares algorithm, and has the fastest convergence speed and training period for neural networks.

(3) Determination of normalized functions

Because the dimensions of the indicators of the training samples are not the same, the numerical values of the different indicators are quite different. All the training processes need to normalize the data in order to speed up the convergence of the network. This article uses the mapminmax normalization function in MATLAB to normalize the data between [-1,1].

5.3.2 Training process

The entire training process of the model will be programmed in MATLAB 2014a. The first 25 groups of data are used as learning data, and the last 3 groups of data are used as test data. In the case of a certain amount of training data and a fixed activation function, the most important influencing factor of the prediction model accuracy is the number of hidden layer nodes, in order to obtain predictions. For the optimal model, the author conducted multiple tests on the node parameters of the network model during the training process.

According to the above, the number of hidden layer nodes is between 5 and 16. In the training process, the assignments of the hidden layer nodes are adjusted to 6, 8, 10, 12, 14, 16 respectively, and the value of the error between the network output and test samples are compared. Each time the network training program given initial weight and threshold is different, so when the training parameters are constant, the error after each training is not the same. Therefore, when the author assigns a value to each node in the training process, the model must be trained 10 times under this node value, and a set of model output values with the smallest error should be selected as the optimal output value under this node number. Table 7 shows the optimal output values and errors for the network prediction with different numbers of hidden layer nodes.

The number of hidden layer nodes	Output value	Actual value	Error	Relative error	Average relative error
	4.9177	5.18	-0.2623	-5.0642%	
6	4.6883	4.78	-0.0917	-1.9190%	-3.063%
	5.2418	5.36	-0.1182	-2.2049%	
	5.0637	5.18	-0.1163	-2.2453%	
8	4.8746	4.78	0.0946	1.9793%	-1.457%
	5.1400	5.36	-0.2200	-4.1044%	
	5.0263	5.18	-0.1537	-2.9681%	
10	4.7612	4.78	-0.0188	-0.3932%	-2.181%
	5.1895	5.36	-0.1705	-3.1808%	
	5.0715	5.18	-0.1085	-2.0938%	
12	4.7889	4.78	0.0089	0.1862%	-1.050%
	5.2934	5.36	-0.0666	-1.2418%	
	5.0480	5.18	-0.1320	-2.5479%	
14	4.6351	4.78	-0.1449	-3.0322%	-1.502%
	5.4176	5.36	0.0576	1.0753%	
	4.9942	5.18	-0.1858	-3.5863%	
16	4.7018	4.78	-0.0782	-1.6354%	-3.463%
	5.0830	5.36	-0.2770	-5.1672%	

Table 7 Corresponding optimal output values and errors for different hidden layer nodes

It can be seen from Table 7 that for the three sets of gas emission quantity test data, when the number of hidden layer nodes is 12, the average relative error of the output values of the three sets of test data corresponding to the prediction model is the smallest, which is 1.05%. The maximum relative error in the data is 2.0938% and the minimum is 0.1862%. Therefore, from a comparison point of view, when the number of nodes in the hidden layer is set to 12, the prediction model for gas emission from fully mechanized mining is the best.

The model training program code is as follows:

```
clear all
clc
% Import training sample data
num=xlsread('train_data.xlsx','B2:R29');
input_train=num(1:25,1:16)';
output_train=num(1:25,17)';
% Data normalization
[inputn,inputps]=mapminmax(input_train);
[outputn,outputps]=mapminmax(output_train);
% Create BP neural network and set network model parameters
net=newff(minmax(inputn),[12,1],{'logsig', 'purelin'},'trainlm')
net.trainparam.show = 50 ;
net.trainparam.epochs = 500 ;
net.trainparam.goal = 0.01 ;
net.trainParam.lr = 0.01 ;
net.trainParam.mc = 0.9 ;
% Training network
net=train(net,inputn,outputn);
% % Save the network
save('TR.mat','net','inputps','outputps');
% Export training model
load 'TR.mat';
% Import Test Data
num=xlsread('test_data.xlsx','B2:Q4');
input_test=num(1:3,1:16)';
inputn_test=mapminmax('apply',input_test,inputps);
an=sim(net,inputn_test);
BPoutput=mapminmax('reverse',an,outputps);
```

The corresponding model framework of the program is shown in Figure 13:

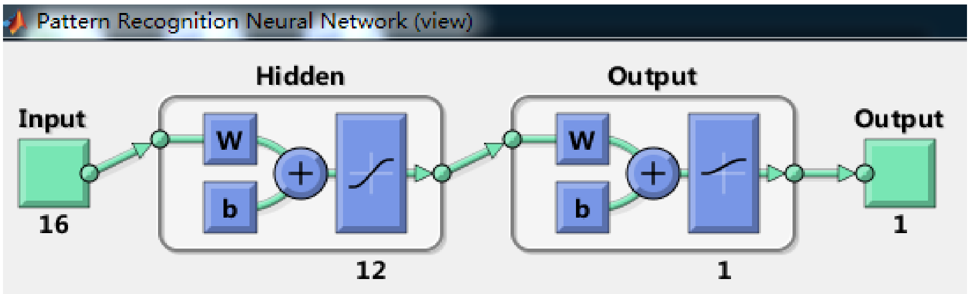


Figure 13 BP neural network prediction model framework of gas emission in fully mechanized face

The model training results are shown in Figure 14:

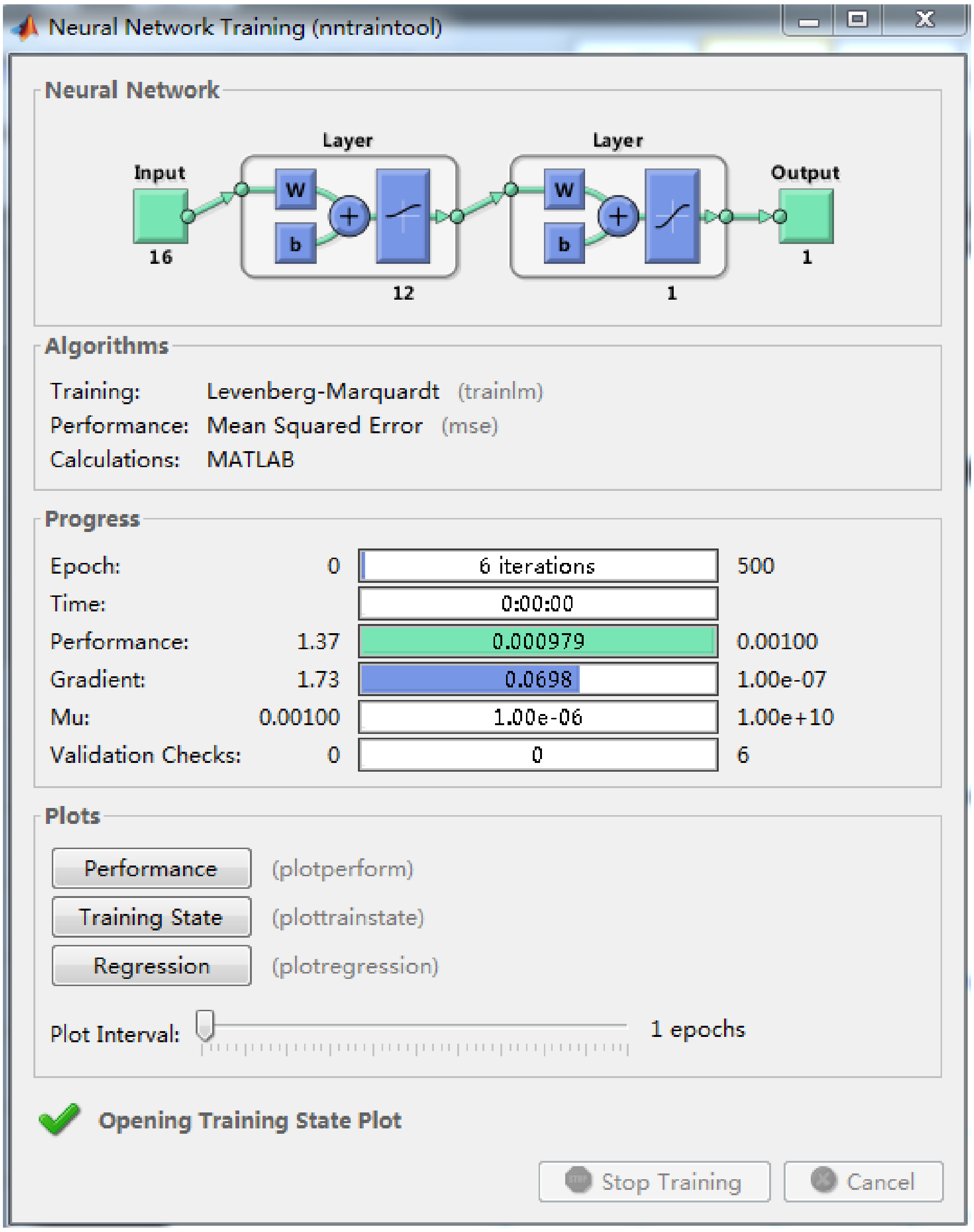
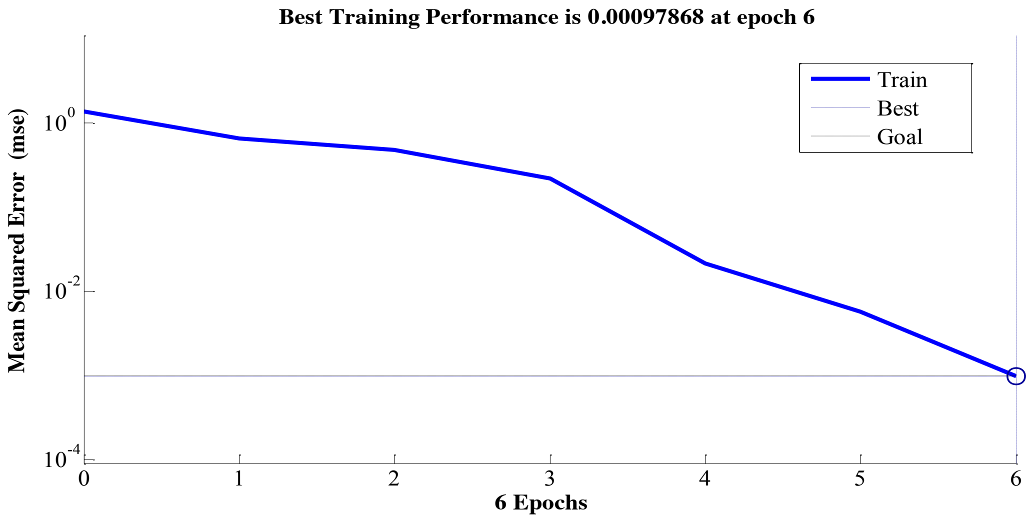


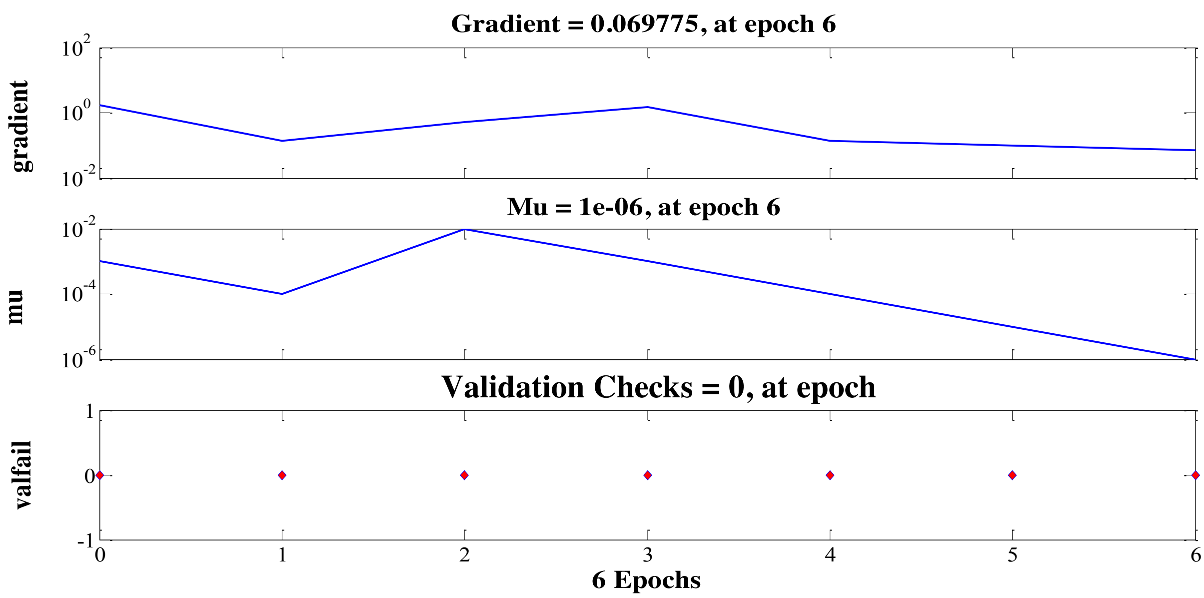
Figure 14 The training results of predictive model

Figure 14 is the interface for training completion. The Algorithms column shows that the model uses the trainlm training function, which corresponds to the Levenberg-

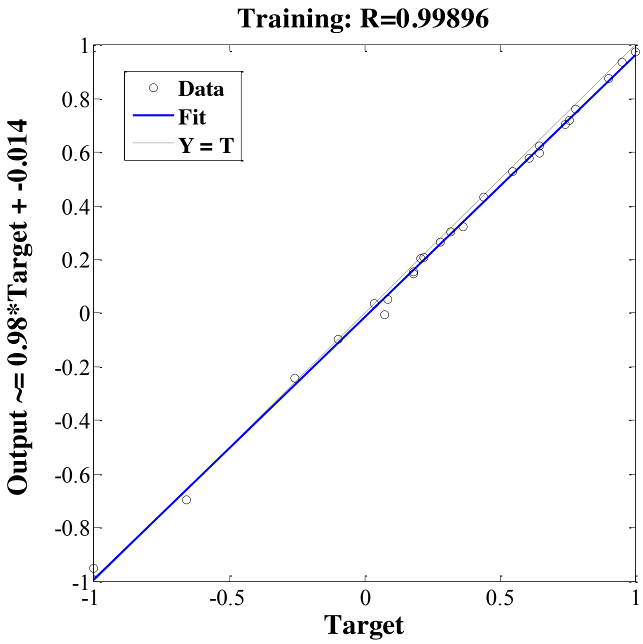
Marquardt algorithm. The performance of the model is examined by Mean Squared Error. From the Progress column, we can see that the initial mean squared error is 1.37. During the training process, the error propagation reaches the set goal (goal=0.001) after 6 iterations. At this point, training ends. The initial performance gradient was 1.73 and dropped to 0.0698 at the end of training. In the Plots column, click on the Performance, Training, and Regression buttons to get a graph of the performance parameters of the training process model, as shown in Figures 15(a), (b), and (c), respectively.



(a) Variation of Mean Square Error (MSE)



(b) Variation of training function parameters



(c) Linear fitting of output values and target values

Figure 15 Changes in model preformance parameters during training

In conjunction with Figure 14, Figure 15(a) shows that the mean squared error (MSE) reaches the set target value during the sixth iteration of the training process, so the training is completed. Figure 15(b) shows that at the end of the model training (sixth iteration), the gradient of the Levenberg-Marquardt algorithm is reduced from the original 1.73 to 0.069775; the algorithm optimization factor mu is reduced from the initial 10-3 to 10-6; the verification fails 0 times. Figure 15(c) shows that the fitting effect of the model's output values and training sample values during training is very good, indirectly indicating that the accuracy of the model is relatively high.

The optimal network model with a hidden layer number of 12 is saved, and the actual prediction of gas emission from the work surface is performed next. The weights and thresholds corresponding to the optimal model are derived from the MATLAB function as follows:

Input layer and hidden layer weights:

{-0.9626 0.2926 -0.2428 0.0261 -0.8632 0.6997 0.3442 0.4140 -0.1273 -
0.0228 -0.0927 0.0749 -0.1775 0.2143 0.0504 0.5923;

-0.0578 -0.2043 0.1726 0.1699 -0.5196 -0.8796 0.0008 0.6203 -0.0352 -
0.6135 0.1623 -0.3743 0.4055 0.6212 -0.3965 -0.0635;

0.3401 -0.6974 0.5527 0.5410 -0.5106 0.2843 0.2099 -0.2756 -0.0975
0.3138 0.2113 -0.0637 0.0848 0.3904 -0.4535 -0.5909;

0.4314 -0.2839 0.6413 0.1210 -0.3852 -0.3929 0.5132 -0.3948 0.7154 -
0.2505 0.1770 0.4136 -0.1904 -0.4714 -0.2823 0.3713;

-0.4058 -0.4329 0.8308 -0.5629 0.1892 -0.2580 0.4169 0.5045 0.1863 -0.5310 0.0526 0.5850 -0.1812 -0.4291 -0.1309 0.1838；

0.1648 -0.3052 -0.1470 0.4555 0.4738 -0.2674 -0.3494 -0.0922 -0.1593 0.6750 -0.0635 -0.2327 -0.7688 0.6353 0.2065 -0.5993；

0.6128 0.1103 -0.4308 0.1380 0.3961 -0.3666 0.3957 -0.1628 0.6846 -0.0628 -0.0897 0.5952 -0.0346 -0.3631 0.6252 0.5566；

0.1598 0.1123 0.1510 -0.1929 0.4227 -0.0657 -0.4109 0.7121 -0.3705 -0.0793 0.0985 0.5408 0.1838 0.8486 -0.3374 -0.7788；

-0.0598 -0.1721 -0.5553 -0.2297 0.2632 0.5715 0.1937 0.1763 0.2235 -0.8745 -0.1115 -0.5400 -0.6129 0.3024 0.1641 -0.4437；

-0.0201 -0.4245 -0.2866 -0.4159 0.3672 -0.1211 0.0677 0.5719 0.6777 -0.1158 -0.0797 0.5002 -0.1363 -0.4796 0.5752 0.8016；

0.5087 0.8611 -0.2444 0.0554 0.7445 0.2017 0.2908 0.1478 0.2748 -0.2901 0.1684 0.6405 -0.2978 -0.0835 0.1990 0.0072；

-0.7693 0.3447 0.4864 -0.2324 -0.5021 -0.0458 0.0991 -0.7049 -0.3886 -0.2212 0.0979 0.6113 -0.1227 0.0733 -0.8258 0.0982；}

Hidden layer threshold：

{1.5141 1.2627 -0.5740 0.5032 -0.2137 -0.2399 0.5491 0.6395 -1.1312 1.5202 -1.5544}

Hidden layer and output layer weight：

{-0.2160 0.2624 -0.3955 0.0623 0.0835 -0.1002 0.0112 0.2599 -0.0768 -0.1434 0.2913 -0.4868}

Output layer threshold：{-0.2715}

5.4 Prediction by the BP neural network model of gas emission quantity from the fully mechanized working face

This section mainly predicts the gas emission from the 81505 fully mechanized coal mining face of the newly invested Baode Mine in 2017. The data collected by the authors on the influencing factors of gas emission from the 81505 working face are shown in Table 8:

Raw gas content in mining layer（m^3/t）	Burial depth of coal seam(m)	Thickness of coal seam(m)	Inclination angle(°)	Length of working face(m)	Advance speed（m/d）	Recovery rate	Raw gas content in adjacent layer（m^3/t）
5.05	270.00	6.70	10.00	240.00	3.52	0.87	4.64
Thickness of adjacent layer(m)	Spacing between layers(m)	Roof management method	Output of working face（t/d）	Gas drainage volume in goaf（m3/min）	Gas drainage volume of working face(pre-extraction)（m3/min）	Air volume（m3/min）	Ground pressure(hPa)
1.82	27.50	1.00	3435.00	11.50	3.59	2521.00	1029.84

Table 8 Gas emission influencing factor data of 81505 working face

In MATLAB, the trained optimal prediction model is invoked to import the gas data of the 81505 working face. The running program can predict the gas emission quantity of the 81505 working face. The forecasting procedure is as follows:

```
% Export training model;
load 'TR.mat';
% Import test data;
num=xlsread('predict_data.xlsx','B2:Q4');
input_predict=num(1:1,1:16)';
inputn_predict=mapminmax('apply',input_predict,inputps);
an=sim(net,inputn_predict);
% Get predicted value;
PREDICT=mapminmax('reverse',an,outputps);
```

The forecast result is shown in Figure 16.

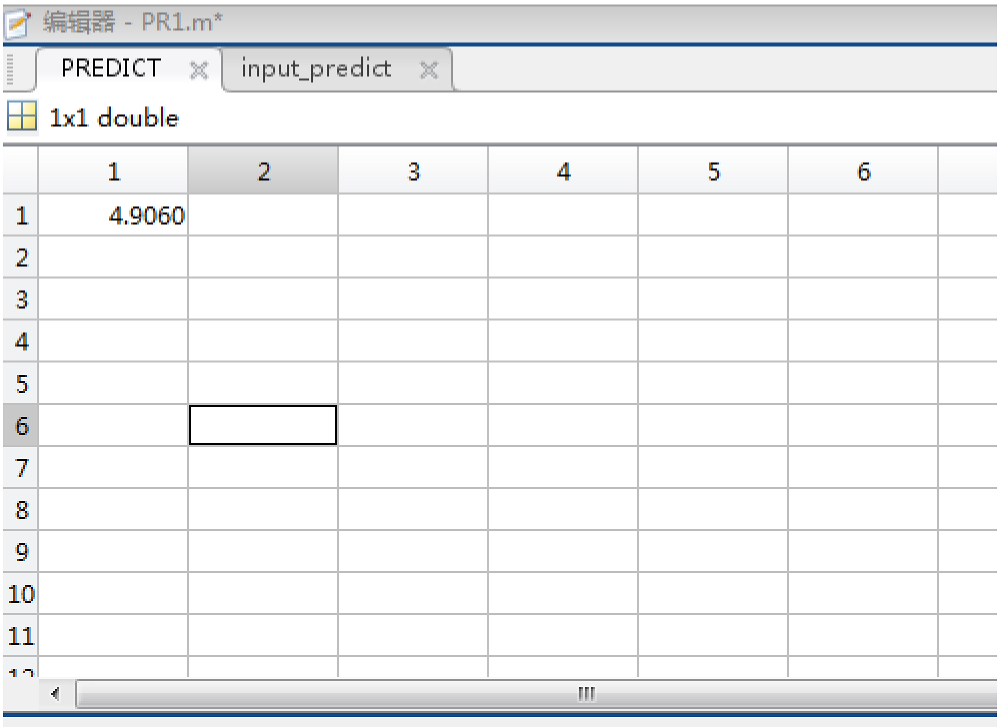


Figure 16 Prediction result

According to data from the Baode Mine, the gas emission from the 81505 face of the Baode Mine is currently in the range of 4.8-5.3 m3/min, so the predicted value based on the BP neural network basically conforms to the mine's actual situation, which means it can provide reference for the development of mine gas control measures. In addition, if the 81505 face is in the mining process, and some of the geological, production process parameters have undergone major changes, or the adjacent layer 81506 face is in mining early process, you can also use this method to predict the gas emission volume of the work surface. Hereby, it is recommended that the Baode Mine Safety Production Department make a detailed record and time series data of the gas in the coal mine working face according to the time changes, so that this method can be used to achieve continuous and real-time forecasting of gas emission from the working face in the actual production.

6 Conclusion and prospective

In this paper, the prediction of gas emission from the 81505 working face of Baode Mine is the main research content. Based on the data collected at the coal mine site, artificial neural network is used as the main research method, and different prediction models are established respectively. The effectiveness and feasibility of the predictive model have been verified. The results of the present summary study are as follows:

(1) Firstly, the influencing factors of gas emission from fully mechanized coal mining face were analyzed from four aspects: geological structure, mining process, production process and natural environment, and a data index system for the influencing factors of gas emission from working face was established. Including 16 quantifiable third-level indicators, namely the raw gas content of the mining layer, the amount of gas drainage from the goaf, the length of the working face, the output of the working face, the depth of the coal seam, the advance speed of the working face, the thickness of the coal seam, the roof management method, adjacent layer thickness, surface atmospheric pressure, working surface air volume, working surface recovery rate, raw gas content in adjacent layers, coal seam inclination angle, working face gas drainage volume (pre-extraction), layer spacing.

(2) Using the grey correlation analysis method to calculate the correlation degree of each influencing factor index of the gas emission rate of the working face, and the calculation result shows that the correlation coefficient of the 16 influencing factor indicators of the gas emission amount of the working face is all above 0.6, all of them have a strong correlation with the gas emission volume at the working face, which verifies the feasibility of the BP neural network prediction model for gas emission from the working face.

(3) Establish a BP neural network prediction model for the quantity of gas emission from the working face. After training and investigation, when the number of hidden layer nodes is set to 12, the prediction effect of the model is optimal. Then, using the best trained prediction model, the prediction of the gas emission from the newly exploited 81505 fully mechanized coal mining face in Baode Mine is predicted. The prediction result is 4.906 m3/min. The prediction results are in line with the actual conditions of the coal mine and prove the feasibility of the method.

The BP neural network prediction model of working face established in this paper have been validated and have good prediction effect on gas emission and gas concentration. However, limited by the experimental conditions and the length of the paper, coupled with my limited ability, the paper still has some deficiencies that require more in-depth research.

With regard to the BP neural network prediction model for the amount of gas emission from the working face, the number of training samples is not large enough due to the conditions, and the generalization ability of the model is not high enough. If we can make a periodic record of the impact index of gas emission during the production process of coal mines so as to obtain a larger capacity training sample, the model will have a better prediction effect. In addition, due to my limited research capacity, the factors affecting the gas emission from the work surface are not comprehensive enough, resulting in a limited number of selected impact indicators. Therefore, the data indicator system of the factors affecting the gas emission from the work surface needs further study to improve.

Reference

1. Yin Wentao, Fu Gui, Yuan Shasha, Dong Jiye. Research on Characteristics and Occurrence Laws of Heavy Gas Explosion Accidents in China from 2001 to 2012 [J]. Chinese Journal of Safety Science, 2013,23(02):141-147.

2. Airey E M. Gas emission from broken coal：An experimentation and theoretical investigation [J]. International Journal of Rock Mechanics and Mining Science, 1968(15): 475-494.

3. Lin Boquan，Li Shugang. Mine gas prevention and utilization [M]. China University of Mining and Technology Press，2014.

4. Huang Ming. Study on Predication and Prediction of Gas Precipitation in Huair Coal Mine [J]. Coal Mine Modernization, 2014, (06): 44-45.

5. Xu Tao，Hao Binbin，Zhang Hua. Application of Sub-source Prediction Method in Prediction of Gas Emission from Newly Built Mines [J]. Coal Technology, 2009, (07): 104-106.

6. Wang Lei，Wang Ruqiong，Qu Hongfeng，al. Improvement and Application of BP Neural Network Algorithm [J]. Software Guide, 2016, (05): 38-40.

7. Huang Shangqing，Zhao Zhiyong，Sun Libo. Improvement of BP Neural Network Algorithm [J]. Science and Technology Innovation Report, 2017, (20): 146-147.

8. Hassan S, Khosravi A, Jaafar J. Variance-covariance based weighing for neural network ensembles[C]//Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on. IEEE, 2013: 3214-3219.

9. Siswantoro J, Prabuwono A S, Abdullah A, et al. A linear model based on Kalman filter for improving neural network classification performance[J]. Expert Systems with Applications, 2016, 49: 112-122.

10. Sheng X. One new error function to improve the neural network learning algorithm [J]. Journal of Interdisciplinary Mathematics, 2017, 20(4): 1101-1110.

11. McCulloch W S, Pitts W. A logical calculus of the ideas immanent in nervous activity[J]. The bulletin of mathematical biophysics, 1943, 5(4): 115-133.

12. Jiao Licheng, Yang Shuyuan, Liu Fang,al. Neural Network Seventy Years: Review and Prospect [J]. Journal of Computer, 2016, 39(8): 1697-1716.

13. Yan Hong, Guan Yanping. Method of Determining the Number of Hidden Layer Elements in BP Neural Network and Examples [J]. Control Engineering, 2009, (S2): 100-102.

14. Shen Huayu, Wang Zhaoxia, Gao Chengyao, al. Determination of Number of Hidden Layer Units in BP Neural Networks [J]. Journal of Tianjin University of Technology, 2008, 24(5): 13-15.

15. Jiao Bin, Ye Mingxing. Method for determining the number of hidden layer units in BP neural network [J]. Journal of Shanghai Institute of Electrical Engineering, 2013, 16(3): 113-116.

16. Qin Yujin. Research and Application of Gas Occurrence Characteristics and Desorption Law in Deep Coal Seams [D]. Fu Xin: Liaoning University of Engineering and Technology, 2012.

17. He Huaping. Field Measurement and Analysis of Gas Source and Distribution Law in Fully Mechanized Face [J]. Industrial Safety and Environmental Protection, 2015, (10): 68-71.

18. He Yuxiong. N1102 Measure and Analysis of Gas Sources in Fully Mechanized Caving Faces [J]. Coal technology, 2015, (3): 153-155.

19. Cui Hongqing, Fan Shuaishuai, Guan Jinfeng. Dividing Source Calculation of Gas Emission at Coal Face [J]. Chinese Journal of Safety Science, 2015, 25(10): 78-83.

20. Ji Zhenguang. Application of Pressure Relief Range and Gas Flow Law in Upper Adjacent Stratum [D]. Taiyuan University of Technology, 2011.

21. Li Yukui. Structure coal gas adsorption, Desorption and Diffusion Characteristics [D]. Jiaozuo: Henan Polytechnic University, 2015.

22. Wang Hongwu. Gas emission law and treatment technology in fully mechanized top coal caving mining face [D]. Inner Mongolia University of Science and Technology, 2017.

23. Pa Shusen. Analysis of Influence Factors of Mine Gas Emission [J]. Enterprise Technology Development: Mid-term, 2014, 33(5): 179-180.

24. Zhu Shifei, Qin Yunhu, Xu Tiangao. Analysis of Influence Factors of Mine Gas Emission [J]. Geological Journal, 2011, 35(1): 86-89.

25. Gao Haiying. Influence of geological factors on gas emission [J]. Inner Mongolia Coal Economy,2017,(01):153-154.

26. Yan Aihua. Multi-source Data Analysis and Prediction of Coal Seam Content [D]. China University of Mining and Technology(Beijing) ,2010.

27. Liang Huazhen, Zhang Guodu. Research and Application of Prediction of Gas Emission from Face [D]. Anhui University of Science and Technology, 2007.

28. Xin Chengpeng. Influence of Gas Displacement Law and Influence of Atmospheric Pressure on Gob of Fully Mechanized Face [D]. Qingdao: Shandong University of Science and Technology, 2009.

29. Zhang Xiang. Prediction of Gas Emission from Coal Face Based on GA-RBF Algorithm [D]. Huainan: Anhui University of Science and Technology,2013.

30. Qi Deming. Analysis and Prediction of Influencing Factors of Coal Mine Gas Emission [J]. Shandong Coal Technology,2018,(01):99-101.

31. Tian Min, Liu Sifeng, Bu Zhikun. Research Summary of Grey Correlation Degree Algorithm Model [J]. Statistics and Measurement, 2008, 2008(1): 24-27.

32. Cybenko G. Approximation by superpositions of a sigmoidal function[J]. Mathematics of control, signals and systems, 1989, 2(4): 303-314.

33. Funahashi K I. On the approximate realization of continuous mappings by neural networks[J]. Neural networks, 1989, 2(3): 183-192.

34. Hornik K, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators[J]. Neural networks, 1989, 2(5): 359-368.

List of Figures

List of Tables

Thesis Grade

Thesis: Prediction of Methane Emission Quantity Based on Back-Propagation Neural Network

Author: Yuchen Fan

Supervisor	Zhu Hongqing	Grade	91	signature	朱红青
Co-supervisor	Nikolaus Sifferlinger	Grade		signature	