

## Research Article

# Prediction Method of Coal Dust Explosion Flame Propagation Characteristics Based on Principal Component Analysis and BP Neural Network

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To study the flame propagation characteristics of coal dust explosion, principal component analysis and BP neural network are used to predict the farthest distance and the maximum speed of flame propagation. Among the eight influencing factors of flame propagation characteristics, three principal components are extracted and named “the factor of volatility,” “the factor of intermediate diameter,” and “the factor of environmental temperature.” By using BP neural network, it is found that the minimum prediction error of the farthest distance of flame propagation is 2.4%, and the minimum prediction error of the maximum speed of flame propagation is 0.4%, which also proves the necessity of principal component analysis by comparing the prediction errors. The research results provide a theoretical method for predicting the flame propagation characteristics of coal dust explosion.

## 1. Introduction

Coal dust explosion is a major accident in safety production of coal mine, and it can destroy the ventilation system of coal mine and put the mine production in a stagnant state. At present, the research on the propagation characteristics of coal dust explosion mainly focuses on the explosion pressure and flame propagation process [1–3]. When coal dust explodes, strong shock waves and flames can be generated due to high temperature and high pressure [4, 5]. Therefore, the flame propagation characteristic of coal dust explosion is an important parameter reflecting the intensity of the explosion [6, 7]. At the same time, understanding the flame propagation characteristics is of great significance for coal mine safety production.

Research on the propagation characteristics of coal dust explosions in confined space shows that coal dust explosion is a complex and extremely rapid physical and chemical conversion process [8–11]. After coal dust particles are rapidly oxidized and burned, the flame temperature is very high, which can reach 2300~2500 K and the pressure can reach 0.7~0.8 MPa in a short time. Gao et al. found that the particle size distribution has a significant effect on the flame

propagation of coal dust explosions [12]. Oran studied the influence of the thickness of the dust layer on the intensity of a dust explosion [13]. Some researchers revealed that the particle dispersion, the particle cloud concentration, and the size of the explosion space have an impact on the explosion flame structure [14–18]. It can be seen that the flame characteristics of dust explosion are affected by many factors, and a slight change in these factors will result in a change in the flame propagation characteristics.

The research methods of coal dust explosion propagation characteristics mainly include experimental analysis, mathematical modeling, and numerical simulation. In recent years, to reveal the flame propagation characteristics of coal dust explosion, the numerical simulation method of coal dust explosion propagation characteristics based on CFD theory is applied to engineering [19]. Establishing the mathematical model that can describe the propagation characteristics of coal dust explosion is the basis for numerical simulation [20–24]; the turbulent flow model of the gas phase and the particle phase, the heat radiation model, and the turbulent combustion model have been established, which provides a theoretical basis for the development of CFD simulation. At the same time, some researchers use the

neural network model to make predictions and get great results [25, 26], which proves that the neural network method can also be used to predict the flame propagation characteristics of coal dust explosions.

In this paper, the authors take the flame propagation characteristics of coal dust explosion as the research object. Considering that there are many factors that affect coal dust explosions, principal component analysis of these factors can extract the principal components that have a greater impact on the flame propagation characteristics of coal dust explosion, and then the BP neural network is used to train the principal components that affect coal dust explosion and the explosion flame propagation characteristics, so as to achieve the prediction of explosion flame propagation characteristics.

## 2. Experiment and Prediction Method

*2.1. Experiment.* In order to predict the flame propagation characteristics of coal dust explosion, it is necessary to test two aspects of experimental data. On the one hand, it is to test the data of the factors affecting the flame propagation characteristics of coal dust explosion, which mainly include industrial analysis index, environmental index, and particle size index. On the other hand, it is to test the data of flame propagation characteristics, which mainly include the farthest distance of flame propagation and the maximum speed of flame propagation.

*2.1.1. Experiment on Influencing Factors of Flame Propagation Characteristics.* The test results of the factors affecting the flame propagation characteristics of coal dust explosion are shown in Table 1. They mainly include eight indexes in three aspects; among them, industrial analysis indexes reflect the composition of coal dust samples, and environmental indexes reflect the temperature and humidity of the explosive environment, while particle size indexes reflect the distribution of coal dust particles. The particle image of No.1 coal sample is shown in Figure 1, and the diameter distribution of coal dust particles is shown in Figure 2. It can be seen that the particle size distribution of coal dust is relatively uniform, and they are all micron-sized. There are a total of eleven coal dust samples, and these data that affect the flame propagation of coal dust explosion are the basis for establishing a prediction model.

*2.1.2. Experiment on Flame Propagation Characteristics.* The experimental apparatus of coal dust explosion flame propagation characteristics is shown in Figure 3, and it is mainly composed of glass pipeline, dust cleaner, air chamber, micro-air compressor, coal sample tube, thermocouple, platinum wire, heater, and camera. The glass tube is open at both ends, the tube length is 1.4 m, the bottom inner diameter is 80 mm, the tube wall thickness is 3 mm, and the length scale is marked on the tube wall in mm. The air flow formed by the air compressor carries the coal dust in the sample tube into the glass tube to form a coal dust cloud, which can cause an explosion in the area near the high-

temperature platinum wire. The spraying pressure is 0.05 MPa, and the ignition temperature is 1100°C. The mass of coal dust put into the sample tube is 2 g. The high-speed camera can be used to collect flame images, so the farthest distance and the maximum speed of flame propagation can be obtained.

### 2.2. Prediction Method

*2.2.1. Principal Component Analysis.* There are eight factors influencing the flame propagation characteristics of coal dust explosion, and there is a certain correlation among these factors, and their effects on the flame propagation characteristics are different. So, if the test data of these influencing factors are directly used to establish a prediction model, there will be great error. Therefore, in this paper, the principal component analysis method is used, which is mainly to reduce the dimensionality of the multivariate data, so that the extracted principal components are not correlated with each other, which will improve the accuracy of the prediction model. The calculation steps of principal component analysis are shown in Figure 4 and are described as follows.

- (1) Determine the eight influencing factors of the explosion flame propagation characteristics of eleven coal dust samples as initial analysis variables.
- (2) According to the initial variables, calculate the covariance matrix for extracting principal components.
- (3) Calculate the eigenvalues and standard eigenvectors of the covariance matrix.
- (4) According to the principle that the cumulative variance contribution rate reaches 85%, the number of principal components is determined, and the expression of principal components is obtained.
- (5) According to the extracted principal components, BP neural network training is further carried out.

*2.2.2. BP Neural Network and Its Improvement.* The BP neural network is a multilayer feedforward network trained according to the error backpropagation algorithm, and its learning ability can express a large number of nonlinear mapping relationships without the need to describe the specific mathematical model of this relationship. Therefore, improving the efficiency and accuracy of BP network training and learning is very important for prediction research [27].

As shown in Figure 5,  $F_i$  is the  $i$ -th principal component of the influencing factors of flame propagation characteristics of coal dust explosion,  $l$  is the farthest distance of flame propagation, and  $v$  is the maximum speed of flame propagation; the learning criterion of BP neural network is the fastest descent algorithm, which means that the network weights and thresholds are continuously adjusted along the gradient descent direction, and finally the error square sum is minimized. The disadvantage is that the BP neural network converges slowly, the training time is long, and it is

TABLE 1: Influencing factors of flame propagation characteristics of coal dust explosion.

Serial number of coal samples	Industrial analysis index (%)			Environmental index		Particle size index ( $\mu\text{m}$ )		
	$M_{\text{ad}}$	$V_{\text{ad}}$	$FC_{\text{ad}}$	$T$ (K)	$H$ (%RH)	$r_1$	$r_2$	$r_3$
1	7.28	36.26	51.54	294	38	65	18	31
2	10.88	32.55	53.25	293	39	37	20	27
3	3.27	30.27	58.94	294	41	29	17	24
4	5.25	34.17	51.68	290	37	30	17	25
5	6.11	31.98	56.22	291	36	35	20	23
6	4.17	36.88	51.70	295	42	46	16	26
7	8.21	33.87	49.62	297	41	37	15	25
8	4.90	37.13	45.33	295	38	35	19	26
9	3.57	39.55	50.60	295	37	30	20	24
10	6.19	35.07	48.76	296	35	39	15	26
11	7.33	34.12	50.28	293	38	26	14	21

$M_{\text{ad}}$ : air-dried moisture;  $V_{\text{ad}}$ : air-dried volatility;  $FC_{\text{ad}}$ : air-dried fixed carbon;  $T$ : environmental temperature;  $H$ : environmental relative humidity;  $r_1$ : average long diameter;  $r_2$ : average short diameter;  $r_3$ : intermediate diameter.

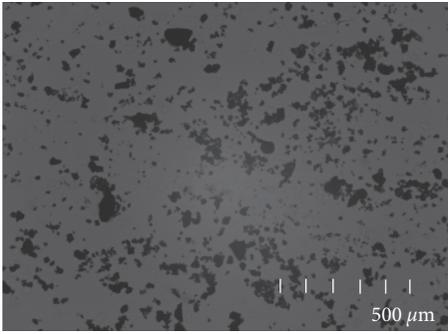


FIGURE 1: Image of coal dust particles (No. 1 coal sample).

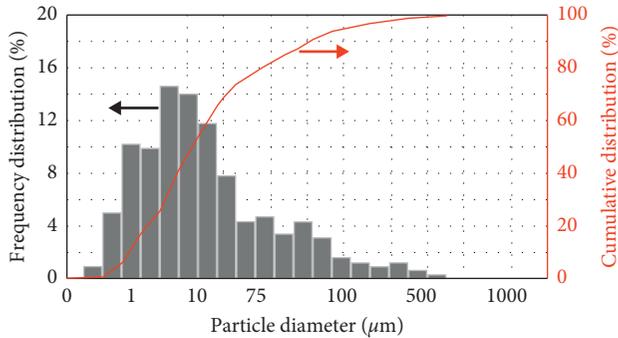


FIGURE 2: Diameter distribution of dust particles (No. 1 coal sample).

easy to cause training failure and make the training result fall into local minimum [28]. Therefore, BP neural network is improved by adopting the additional momentum method, and the network training can improve the training efficiency and accuracy of the BP network by using MATLAB software. The adjustment formula of the additional momentum factor  $w_{ij}$  and the threshold  $b_i$  is as follows:

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

where  $k$  is the number of training times, with a value of 2100;  $M$  is the momentum adjustment factor, with a value of 0.95;

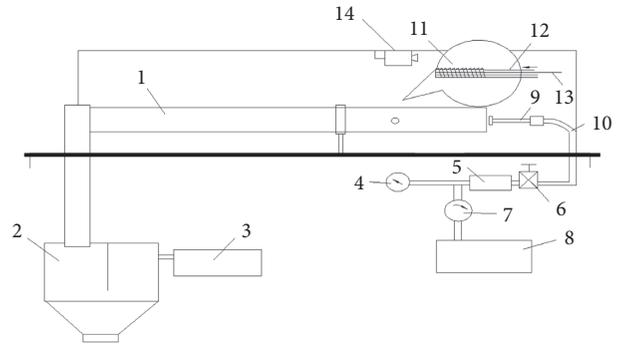


FIGURE 3: Structure of experimental apparatus. 1, glass pipeline; 2, dust collection region; 3, dust cleaner; 4, pressure gauge; 5, air chamber; 6, electromagnetic valve; 7, regulating valve; 8, micro-air compressor; 9, coal sample tube; 10, bent pipe; 11, platinum wire; 12, heater; 13, thermocouple; 14, camera.

$\eta$  is the step length, with a value of 0.05;  $\delta_i$  is the  $i$ -th input variable; and  $P_j$  is the  $j$ -th output variable.

Before training the BP network with the additional momentum method, initialize the correction value matrix of the network weight threshold to a zero matrix and then use the “learn bpm” function to calculate the correction value matrix.

### 3. Results and Discussion

**3.1. Test Result of Flame Propagation Characteristics of Coal Dust Explosion.** According to Section 2.1.2, the flame propagation characteristics of coal dust explosion mainly include the farthest distance of flame propagation and the maximum speed of flame propagation, and the test results are shown in Table 2. It can be seen that the farthest distance of flame propagation and the maximum speed of flame propagation of eleven kinds of coal samples are obviously different, which can provide raw data for BP neural network training.

**3.2. Principal Component Analysis of Influencing Factors of Flame Propagation Characteristics.** Principal component

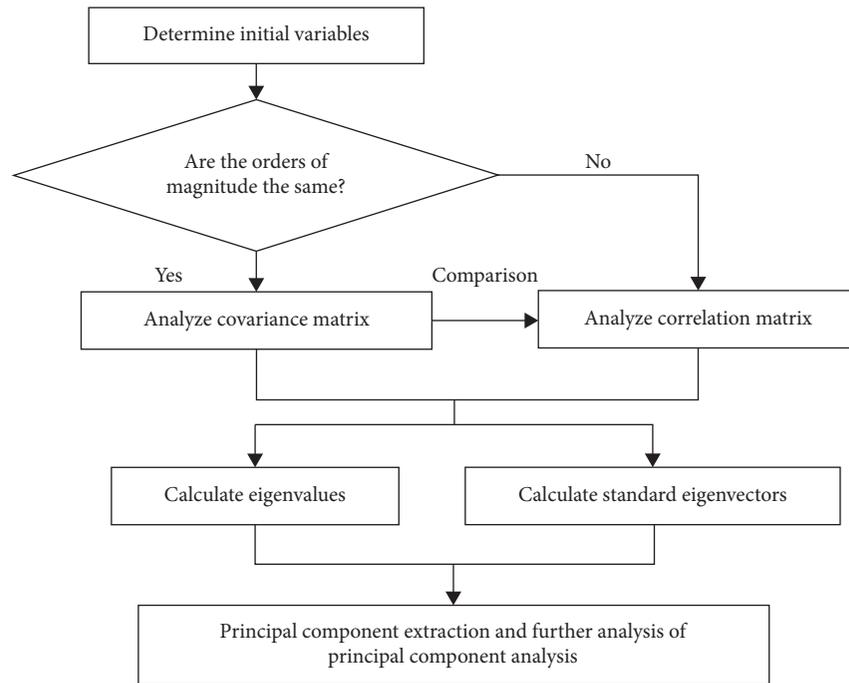


FIGURE 4: Calculation steps of principal component analysis.

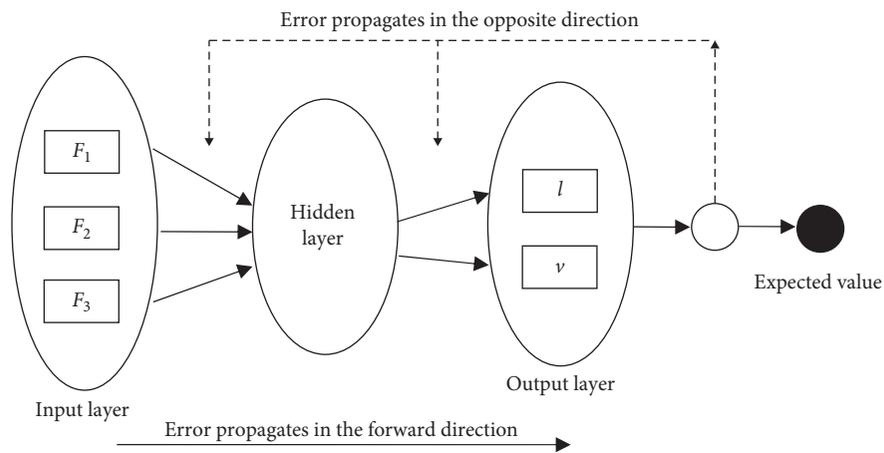


FIGURE 5: BP neural network training process.

TABLE 2: Influencing factors of flame propagation characteristics of coal dust explosion.

Serial number of coal samples	Flame propagation characteristics		Serial number of coal samples	Flame propagation characteristics	
	$l$ (mm)	$v$ (m/s)		$l$ (mm)	$v$ (m/s)
1	47.1	12.5	7	24.8	8.3
2	15.6	3.9	8	43.7	13.7
3	8.2	2.1	9	96.2	37.4
4	26.3	8.7	10	39.8	10.1
5	21.3	6.2	11	18.0	5.1
6	58.0	21.3			

$l$ : farthest distance of flame propagation;  $v$ : maximum speed of flame propagation.

analysis is to generate a series of uncorrelated new variables by constructing a linear combination of the original variables, which select a few new variables from original variables and make new variables reflect as much information as the original variables; in this way, new variables are used to replace the original variables for BP neural network training. So, according to the test data of factors affecting flame propagation characteristics in Table 1, the covariance matrix  $S$  of the test data of the factors influencing the flame propagation characteristics is obtained as follows:

$$S = \begin{bmatrix} 3.6 & -5.8 & -6.4 & 0.51 & 7.7 & -3.9 & -2.4 & 8.4 \\ -5.8 & 32.6 & 36.0 & -32.9 & -34.8 & 2.2 & -2.2 & 50.1 \\ -6.4 & 36.0 & 35.5 & -32.2 & -33.8 & 1.5 & -1.6 & 52.9 \\ 6.3 & -32.9 & -32.2 & 44.3 & 46.2 & -17.7 & -14.6 & -83.2 \\ 7.7 & -34.8 & -33.8 & 46.2 & 48.8 & -18.1 & -14.9 & -70.5 \\ -3.9 & 2.2 & 1.5 & -17.7 & -18.1 & 18.3 & 17.3 & 23.7 \\ -2.4 & -2.2 & -1.6 & -14.6 & -14.9 & 17.3 & 16.5 & 17.6 \\ 8.4 & 50.1 & 52.9 & -83.2 & -70.5 & 23.7 & 17.6 & 1258.7 \end{bmatrix} \quad (2)$$

Because the units of the original data are not uniform, the main diagonal elements of the covariance matrix  $S$  are quite different. If the principal components are extracted according to the covariance matrix  $S$ , the information of the principal components will be concentrated on the variables with larger variances, resulting in loss of information. Therefore, the principal component analysis cannot start from the covariance matrix, and data preprocessing must be considered. So, using the preprocessing method of data standardization, the calculated correlation matrix  $R$  is as follows:

$$R = \begin{bmatrix} 1.00 & -0.52 & -0.49 & 0.51 & 0.60 & -0.48 & -0.31 & 0.13 \\ -0.52 & 1.00 & 0.99 & -0.82 & -0.82 & 0.08 & -0.05 & 0.24 \\ -0.49 & 0.99 & 1.00 & -0.81 & -0.81 & 0.06 & -0.07 & 0.25 \\ 0.51 & -0.82 & -0.81 & 1.00 & 0.99 & -0.60 & -0.52 & -0.35 \\ 0.60 & -0.82 & -0.81 & 0.99 & 1.00 & -0.62 & -0.52 & -0.28 \\ -0.48 & 0.08 & 0.06 & -0.60 & -0.62 & 1.00 & 0.98 & 0.15 \\ -0.31 & -0.05 & -0.07 & -0.52 & -0.52 & 0.98 & 1.00 & 0.12 \\ 0.13 & 0.24 & 0.25 & -0.35 & -0.28 & 0.15 & 0.12 & 1.00 \end{bmatrix} \quad (3)$$

According to the calculation steps of principal component analysis in Section 2.2.1, calculate the eigenvalues and eigenvectors of the correlation matrix  $R$ , and the results are shown in Table 3. The variance contribution rate of the  $k$ -th principal component represents the percentage of information extracted by the  $k$ -th principal component. The cumulative contribution rate of the  $k$ -th principal component represents the percentage of information extracted by the first  $k$  principal components. The cumulative contribution rate of the first three principal components reached 95.01%, indicating that the first three principal components have already reflected 95.01% of the original eight indexes. Therefore, it is determined to extract the first three principal

components to achieve the dimensionality reduction of the original data.

Figure 6 shows eight eigenvalues of principal components; it can intuitively evaluate which principal components account for most of the data variability through the connected polylines. Obviously, the first two segments of polyline have steeper slopes, so the cumulative contribution rate of the first three principal components reaches 95.01%, and it can also be determined to extract the first three principal components.

Among the principal components of the first three standardized samples, the coefficients before each standardized variable are the three orthogonal unitized eigenvectors corresponding to the three eigenvalues. According to the calculated eigenvectors, the expressions of the first three principal components  $F_1$ ,  $F_2$ , and  $F_3$  are obtained as follows:

$$\begin{aligned} F_1 &= -0.3258x_1^* + 0.7804x_2^* + 0.3829x_3^* + 0.4622x_4^* \\ &\quad + 0.4680x_5^* - 0.2963x_6^* - 0.2426x_7^* - 0.1486x_8^*, \\ F_2 &= -0.0455x_1^* - 0.3978x_2^* - 0.4113x_3^* + 0.1024x_4^* \\ &\quad - 0.0001x_5^* + 0.3522x_6^* + 0.3025x_7^* - 0.7505x_8^*, \\ F_3 &= 0.2274x_1^* + 0.0491x_2^* + 0.0237x_3^* + 0.6046x_4^* \\ &\quad + 0.0142x_5^* - 0.1024x_6^* - 0.2191x_7^* - 0.2392x_8^*, \end{aligned} \quad (4)$$

where  $x_i^*$  is the variable of the standardized index corresponding to  $x_i$  ( $i = 1, 2, \dots, 8$ ) and  $x_i$  is the  $i$ -th influencing factor of the flame propagation characteristics of coal dust explosion.

The first principal component  $F_1$  reflects 56.19% of the information of all indexes, and the corresponding eigenvector represents the contribution of each index to the first principal component. The coefficient before  $x_2^*$  in  $F_1$  is the largest and positive, indicating that the index of  $V_{ad}$  has the greatest influence on the explosion flame propagation in the first principal component. Therefore, the first principal component  $F_1$  is named "the factor of volatility." In the same way, the second principal component  $F_2$  is named "the factor of intermediate diameter," and the third principal component  $F_3$  is named "the factor of environmental temperature," and the naming results of the above principal components are shown in Table 4.

### 3.3. BP Neural Network Prediction of Flame Propagation Characteristics.

Because there are three principal components extracted to reflect the influencing factors of flame propagation characteristics, the number of input layer nodes of the BP neural network is determined to be three. Based on the test data in Table 1, there are eleven training samples. Since the flame propagation characteristics of coal dust explosion mainly include the farthest propagation distance and the greatest propagation speed, there are two output layer nodes. Since there is no fixed calculation formula for the number of hidden layer nodes, it needs to be adjusted continuously and finally determined according to the convergence situation. After adjustment, it is finally determined that when the number of hidden neurons is thirteen, the network has the fastest convergence speed and the largest

TABLE 3: Principal component analysis results.

Principal component	Calculation results			Principal component	Calculation results		
	Eigenvalues	Variance contribution rate (%)	Cumulative contribution rate (%)		Eigenvalues	Variance contribution rate (%)	Cumulative contribution rate (%)
$F_1$	4.48	56.19	56.19	$F_5$	0	0	100
$F_2$	1.99	24.79	80.98	$F_6$	0	0	100
$F_3$	1.13	14.03	95.01	$F_7$	0	0	100
$F_4$	0.39	4.99	100	$F_8$	0	0	100

$F_k$ : the  $k$ -th principal component.

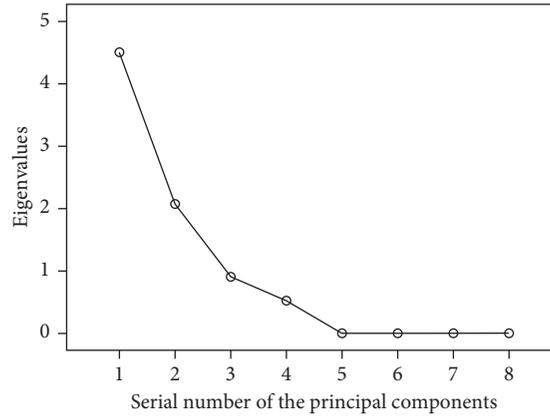


FIGURE 6: Eigenvalues of principal components.

TABLE 4: Naming results of the first three principal components.

Principal component	Mainly reflected indexes	Naming results
$F_1$	$x_2^*$	“The factor of volatility”
$F_2$	$x_8^*$	“The factor of intermediate diameter”
$F_3$	$x_4^*$	“The factor of environmental temperature”

$F_k$ : the  $k$ -th principal component.

prediction accuracy. The transfer function of the hidden layer selected by the BP neural network is “tansig,” and the transfer function of the output layer is “purelin.”

The extracted three principal components of factors affecting flame propagation characteristics of coal dust samples and the test data of flame propagation characteristics in Table 2 are used to train BP network. Before iterative calculation of BP neural network, set the mean square error of BP neural network to 0.01, which means the training accuracy is 0.01. When the iterative training reaches 2229 times, the BP neural network converges, so the training is stopped, as shown in Figure 7.

3.4. Comparative Analysis of Test Result and Prediction Result.

In order to compare the test results with the predicted results, ten coal dust samples are used to test the trained neural network. So, the percentage of samples for the training stage is 52.38%, and the percentage of samples for the testing stage is 47.62%. The data of the factors affecting the flame propagation characteristics of ten groups of coal samples to be tested are brought into the trained BP neural network, and the predicted results of the flame propagation

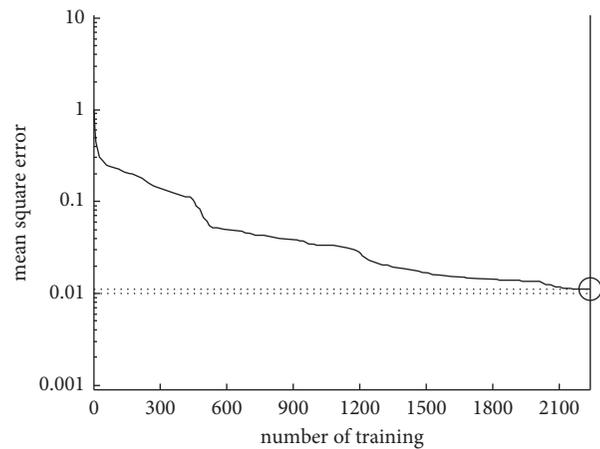


FIGURE 7: Mean square error of network training.

characteristics and the relative errors obtained are shown in Table 5. The flame propagation characteristics and relative errors predicted by using only BP network training without principal component analysis are also given in Table 5.

TABLE 5: Prediction result of BP neural network and relative error.

Number of coal sample	$l$ (mm)	$l_1$ (mm)	$\delta_1$ (%)	$l_2$ (mm)	$\delta_2$ (%)	Number of coal sample	$v$ (m/s)	$v_1$ (m/s)	$\varepsilon_1$ (%)	$v_2$ (m/s)	$\varepsilon_2$ (%)
1	9.3	9.6	3.1	8.4	10.7	1	12.2	13.2	7.6	16.4	25.6
2	6.6	6.4	3.1	7.6	13.2	2	12.6	12.7	0.8	11.5	9.6
3	17.5	16.9	3.5	16.4	6.7	3	24.5	24.6	0.4	23.6	3.8
4	22.3	21.7	2.7	20.1	10.9	4	27.6	28.7	3.8	29.1	5.1
5	23.8	24.8	4.0	26.0	8.5	5	32.3	33.6	3.9	34.2	5.6
6	12.5	12.2	2.4	13.1	4.6	6	17.6	16.5	6.7	20.0	12.0
7	10.1	10.5	3.8	9.2	9.8	7	19.0	20.3	6.4	21.5	11.6
8	19.6	19.0	3.2	17.0	15.3	8	24.8	25.1	1.2	27.7	10.5
9	8.6	8.9	3.3	9.0	4.4	9	14.1	14.9	5.4	12.8	10.2
10	6.2	6.4	3.1	7.5	17.3	10	10.2	9.4	8.5	12.7	19.7

$l$ : test result of farthest distance of flame propagation;  $l_1$ : farthest distance of flame propagation predicted by using both principal component analysis and BP network;  $\delta_1$ : prediction error of farthest distance of flame propagation by using both principal component analysis and BP network;  $l_2$ : farthest distance of flame propagation predicted by using only BP network;  $\delta_2$ : prediction error of farthest distance of flame propagation by using only BP network;  $v$ : test result of maximum speed of flame propagation;  $v_1$ : maximum speed of flame propagation predicted by using both principal component analysis and BP network;  $\varepsilon_1$ : prediction error of maximum speed of flame propagation by using both principal component analysis and BP network;  $v_2$ : maximum speed of flame propagation predicted by using only BP network;  $\varepsilon_2$ : prediction error of maximum speed of flame propagation by using only BP network.

It can be seen from Table 5 that by adopting the principal component analysis method, the maximum prediction error of the farthest distance of flame propagation is reduced from 17.3% to 3.1%, and the minimum is only 2.4%; the maximum prediction error of the maximum speed of flame propagation is reduced from 25.6% to 7.6%, and the minimum is only 0.4%; the prediction errors are acceptable.

So, it can be concluded that by using the developed model of principal component analysis and BP neural network, the training speed of the BP network can be accelerated, and the prediction results are more accurate. Besides, the developed model has some disadvantages. For example, the error of the prediction result depends on the number of training samples of the BP neural network. If the number of samples is not enough, the error of the prediction result of the developed model will become larger. The current predicting study is limited by the number of coal dust samples, the extraction results of principal components, and the training accuracy of BP neural network. The research results have a certain significance for understanding the influence of different factors on the flame propagation characteristics of coal dust explosion and provide a theoretical method for predicting the explosion flame propagation characteristics.

#### 4. Conclusions

In this paper, eleven coal dust training samples and ten coal dust testing samples are selected for the experiment of coal dust explosion. The principal component analysis method and the BP neural network prediction method are used to predict the flame propagation characteristics of coal dust explosion. The conclusions can be summarized as follows.

The principal component analysis method is used to extract the principal components of the influencing factors of the flame propagation characteristics of coal dust explosion. According to the first three principal components, the cumulative contribution rate is 95.01%, and it is determined to extract three principal components.

According to the expressions of three principal components of the influencing factors of flame propagation characteristics, three principal components are named "the factor of volatility," "the factor of intermediate diameter, and" "the factor of environmental temperature."

BP neural network is improved by adopting the additional momentum method, and the prediction errors of the flame propagation characteristics are within the acceptable range. By comparing the errors predicted by using only BP network training without principal component analysis, it is found that principal component analysis can improve the accuracy of prediction results, the minimum prediction error of the farthest distance of flame propagation is 2.4%, and the minimum prediction error of the maximum speed of flame propagation is only 0.4%.

#### Data Availability

The data used to support the findings of this study are included within the article.

#### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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