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Establishment of grey-neural network forecasting model of coal and gas outburst

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Abstract: Effect factors on coal and gas outburst are analyzed using grey correlation method so as to determine the input parameters of artificial neural network (ANN).Then using the improved BP algorithm, we choose five dominant factors of grey correlation analysis as the input parameters to establish neural network model for forecasting coal and gas outburst. This network was trained by using the learning samples collected from the instances of typical coal and gas outburst mines in China. Meanwhile, we take coal and gas outburst instances of Yunnan Enhong coal mine as forecasting samples and compare the forecasting result from these samples with that from the conventional method, indicating that this model can meet the forecasting requirements of coal and gas outburst.

Keywords: coal and gas outburst, grey correlation analysis, influencing factors, forecasting, grey-neural network

1. Introduction

In china, coal has a wide distribution and the landforms of coal fields are complex. The coal production is threatened by water, fire, coal dust, roof fall, gas outburst, and so on. Of these factors, gas outburst is the most serious dangerous one to cause great economic loss and kill coal miners. So, gas outburst forecasting becomes particularly important [1].

Because the inherent mechanism of coal and gas outburst is so complicated and lots of uncertain and fuzzy problems exist between effect factors and accidents, both the traditional forecasting technologies based on experience and the statistical forecasting technologies based on mathematical model are restricted in the field application. Grey-neural network forecasting methods of coal and gas outburst is applied in this paper.

2. Analysis of effect factors

2.1. Initial velocity of gas (Δp)

The initial velocity of gas is one of the risk indexes for coal and gas outburst[2-3]. It shows the blow-off velocity of gas from coal. This index reflects how quickly the gas releases from coal seams. Δp is related to the gas content of coal, structure and surface property of pore. To a large degree, the movement and destructive power of gas is decided by desorption and blow-off ability of gas in coal during the developing process of coal and gas outburst.

2.2. Consistent coefficient of coal (f)

The consistent coefficient of coal is a kind of relative indexes of coal particles' mechanical strength. Its value reflects coal's physical and mechanical properties and is also an important parameter involved in coal and gas outburst. Generally, the bigger the f is, the more difficult the outburst happens under the same gas pressure and ground stress.

2.3. Gas pressure

Ground stress controls gas pressure field and promotes coal-body to be destructed by gas. The increased pressure in surrounding rock determines ventilation property of coal seams and leads to increase pressure gradient which is favorable for the coal and gas outburst to happen. The content of gas pressure is an important symbol of gas compressive energy's value.

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2.4. Thickness of soft sublayer

The deeper the coal seam is, the more frequent the gas outburst happens. Both the outburst times and the scales increase with the increase of coal seam thickness, especially the thickness of the soft sublayer. Because the reason of low mechanical strength of coal and bad ventilation property, much content and pressure of gas exists in the change area of coal bed thickness.

2.5. Coal-body destruction type

Ground stresses, including self-weight stress, structural stress, and disturbance stress, get the surrounding rock's or coal-body's elastic potential energy do work, making the coal-body destroyed and displaced. Coal-body destruction type refers to the coal-body destruction degree of coal-body structure under structural stress. According to the destruction degree, it can be divided into five types: - non-destructive coal; -destructive coal; - strong destructive coal; - pulverized coal; -completely pulverized coal. In the following table they're replaced by 1, 2, 3, 4, and 5, respectively.

2.6. Mining depth

Viewing from the **regional metamorphism** of coal, the depth is the main reason lignite changing into anthracite because, with increase of depth, the pressure and temperature increases. The deeper the depth is, the higher the coal rank is. The huge thickness cover makes the gas be formed and protected, most of which are methane and so on. So the outburst intensity of coal will increase with the increase of mining depth.

2.7 The Gas Content of Coal seam

Gas is from the coal seam, strata, gob or production process during mine excavation. The higher the gas content of coal seam is, the more gas will effuse into tunnels and working faces during coal seam excavation. As a result, the threat of the gas accident will be more serious.

Table 1. Original data of each influencing factor

Sample Number	outburst scales (t)	Initial Velocity (p)	Consistence coefficient (f)	Gas Pressure (MPa)	Soft stratification thickness (m)	Coal-body Destruction Type	Mining Depth (km)	Gas Content of Coal Seam (m^3/t)
1	150.00	19.00	0.31	2.76	1.20	3	0.620	10.02
2	20.60	6.00	0.24	0.95	2.00	5	0.445	13.04
3	15.10	18.00	0.16	1.20	1.30	3	0.462	10.36
4	0.00	5.00	0.61	1.17	1.61	1	0.395	9.04
5	76.50	8.00	0.36	1.25	1.41	3	0.745	9.01
6	10.20	8.00	0.59	2.80	1.82	3	0.425	10.25
7	0.00	7.00	0.48	2.00	1.10	1	0.460	9.50
8	110.20	14.00	0.22	3.95	0.93	3	0.543	8.23

Based on the above factors, this paper collected some typical data from eight outburst mines in China as the sample sets of grey relation analysis model. Values of various factors are shown in table 1.

3. Grey relation analysis

In fact, a series of effect factors of coal and gas outburst are non-time series, so it's reasonable to generate the interval values from original data. This paper makes the factor that is outburst scales of gas as the controller series and other various factors as sub sequence of grey relation analysis.

Getting the interval values from original data according to the formula: $y_i(1) = \dfrac{x_i(1) - \min\limits_i x_i(1)}{\max\limits_i x_i(1) - \min\limits_i x_i(1)}$, then calculating the absolute differences $\Delta_i(k)$ of one sample's interval values between controller series and sub sequence by the formula: $\Delta_i(k) = |x_0(k) - x_i(k)|$. Correlation coefficient series $\xi_i(k)$ can be gotten by the Calculation Formula

$\xi_i(k) = \dfrac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}$ and then the correlation degree between controller series and sub sequence can be gotten though the formula: $r_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k)$. The Resolution Coefficient ρ is 0.5. The results are shown in table2.

Table 2. Relational degree taxis of influencing factors

Influencing factors	Correlation degree	Ordering
Initial Velocity Δp	0.79	1
Consistence coefficient f	0.58	5
Gas Pressure p	0.68	4
Soft stratification thickness	0.54	7
Coal-body Destruction Type	0.70	3
Mining Depth	0.78	2
Gas Content of Coal Seam	0.55	6

The relating sequence of various factors for gas outburst scales shows the affecting degree on the gas outburst scales. According to the calculation results of correlation degree above, correlation degree that various factors for gas outburst scales orders are as follows.

Initial velocity> mining depth> coal-body destruction type> gas pressure> consistence coefficient> gas content of coal seam>soft stratification thickness.

4. Model building

Complicated nonlinear relation exists between various factors and gas outburst scales. Using artificial neural network to forecast the happening coal and gas outburst can reduce the human disturbance, make the result more objective, and show the connection of input and output variables truly[4-5]

4.1. Determination of input elements

The accuracy of neural Network isn't proportional to the number of chosen factors. If factors are overabundant, the learning speed of network will reduce and the learning process will become complicated and difficult to control. At the same time, the number of effect factor can't be too less, otherwise it'll make results depend on some parts of factors too much. We chose five dominant factors in Gray correlation analysis: Initial Velocity, Mining Depth, Coal-body Destruction Type, Gas Pressure, and Consistent coefficient as input **neurons. In addition,** we introduce the improved BP algorithm of Artificial Neural Network and adopt neural network function storehouse of MATLAB to write the procedure and established neural network predicting model of analysis of coal and gas outburst.

4.2. Classification of the forecast results

According to the actual conditions of coal mine, the coal seam can be divided into two types: outburst coal seam and non-outburst coal seam. In order to improve the actual applicability, this paper divided the outburst situation into three types: small amount outburst (below 50t, called small) ;common outburst(between 50t and 100t, called medium);mass outburst(above 100t, called large). The output value of Neural Network training can't be 0 or 1, so the output values are set into four kinds as follows: [1,0,0,0] stands for" non" ;[0,1,0,0] stands for "small" ;[0,0,1,0] stands for "medium" ;[0,0,0,1] stands for " large".

4.3. Determination of network structure

According to the analysis above, we chose five main effect factors of coal and gas outburst and they can also serve as input nodes of the model. There are four output nodes and the output value is 0 or 1.

The number of the hidden layer nodes is very important. If the number of the nodes is too less, the network can't establish complicated judgment boundary; If the number of the nodes is overabundant, the network will lose the summarizing and judging ability [6]. The number of 11, 9 and 16 are tried in this paper.

Finally the best number of hidden layer is chosen by comparing the network performance. The transfer function between different layers is chosen by sigmoid function and the whole interconnection is used between different layers. Network structure of Neural Network is showed in figure 1.

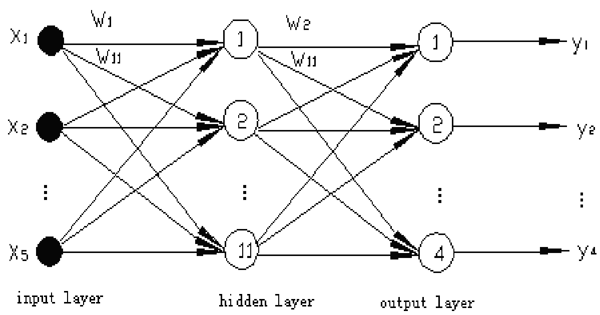

Fig..1. BP network structure chart of coal and gas outburst forecast

4.4. Collection and normalization of data

Typical coal and gas outburst instances must be chosen as sample and their data must be standardized before network training. This paper chose five effect factors from typical coal and gas outburst mines in China as learning samples shown in table 3.

Table 3. Original data of coal and gas outburst instances

Sample Number	Initial Velocity (p)	Consistence coefficient (f)	Gas Pressue （MPa）	Coal-body Destruction Type	Mining Depth（km）	outburst scales
1	19.00	0.31	2.76	3	0.620	Big
2	6.00	0.24	0.95	5	0.445	Small
3	18.00	0.16	1.20	3	0.462	Small
4	5.00	0.61	1.17	1	0.395	Non
5	8.00	0.36	1.25	3	0.745	Medium
6	8.00	0.59	2.80	3	0.425	Small
7	7.00	0.48	2.00	1	0.460	Non
8	14.00	0.22	3.95	3	0.543	Big
9	11.00	0.28	2.39	3	0.515	Small
10	4.80	0.60	1.05	2	0.477	Non
11	6.00	0.24	0.95	3	0.455	Medium
12	14.00	0.34	2.16	4	0.510	Small
13	4.00	0.58	1.40	3	0.428	Non
14	6.00	0.42	1.40	3	0.426	Big
15	4.00	0.51	2.90	5	0.442	big
16	14.00	0.24	3.95	3	5.52	small
17	4.00	0.53	1.65	2	4.38	non
18	6.00	0.54	3.95	5	5.43	big
19	7.40	0.37	0.75	4	7.40	medium
20	3.00	0.51	1.40	3	4.00	Non

Input nodes' parameter values of the BP network are different and the values diverge greatly, so the values need to be normalized in order to prevent the information of small values from being weakened by big ones. Generally, various values are normalized between 0 and 1. But it isn't an appropriate method for this case. Because the function sigmoid curve changes is smooth between 0 and 0.1 or between 0.1 and 0.9. So the good normalized value range should be [0.10,0.90]. The formula of $\frac{X-\min}{\max-\min}\times 0.8+0.1$ can satisfy the normalized requirements. Quantificational data can be normalized using the above method.

4.5. Training of BP Neural Network for coal and gas outburst prediction

In this paper, the BP tool functions in the ANN toolbox of MATLAB software is applied, and applications of some important tool functions are demonstrated[7-10]. The inputting layer has five nerve fibres because the inputting samples are 5-dimensional inputting vector. After many times pilot calculation, the high performance network will be gotten if the number of hidden layer is 11. The outputting layer has four neurons because of four outputting data. So the network's structure is 5-11-4. The transfer function between different layers is the S-shaped tangent function.

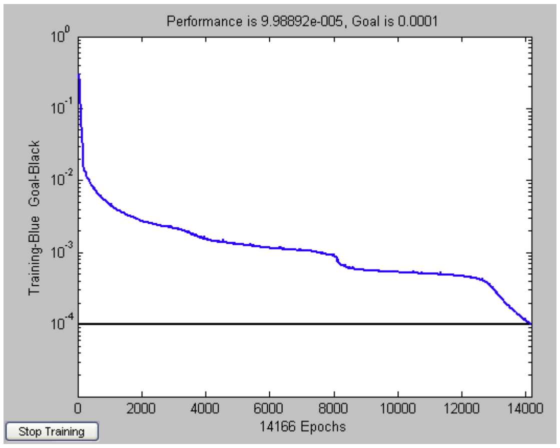

Fig. 2. Training error curve of network

The training function is *traingdx* and the learning rate is adapted by network itself, called improved BP algorithm. The training error curve of network is shown in figure 2. From the figure we can get that the network converges after 14,166 times iterative calculations and the network also can identify the study learning sample completely and accurately. Complicated nonlinear relation is set up between various factors and gas outburst scales.

4.6. Coal and gas outburst forecasting by trained network

Eight coal and gas outburst instances of Yunnan Enhong coal mine were used as forecasting samples. The detail data are showed in table 4.When the network outputting value is close to [1, 0, 0, 0], the scale of coal and gas outburst is "small", when the network outputting value is close to [0, 1, 0, 0], the scale is "Medium", when the network outputting value is close to [0, 0, 0, 1], the scale is "big".

Network output is as follows:

```
Out =
    Columns 1 through 8
    0.0214  0.0035  0.0743  0.0249  0.0556  0.0174  0.0025  0.0064
    0.9986  0.9999  0.9676  0.9995  0.9849  0.9926  0.9999  0.9979
    0.0266  0.0170  0.0368  0.0333  0.0301  0.0258  0.0135  0.0309
    0.0154  0.0123  0.0712  0.0044  0.0556  0.0860  0.0196  0.0630
```

The expected outputting values of BP network should be all [0,1,0,0], from forecast results, they are all consistent with actual coal mine situation. So the method has certain practicability. The Error curve is shown in figure 3.

The forecasting results calculated by grey - neural network and other methods are shown in table 5, in which "You" means having the risk of coal and gas outburst while "Wu" means having no risk of outburst.

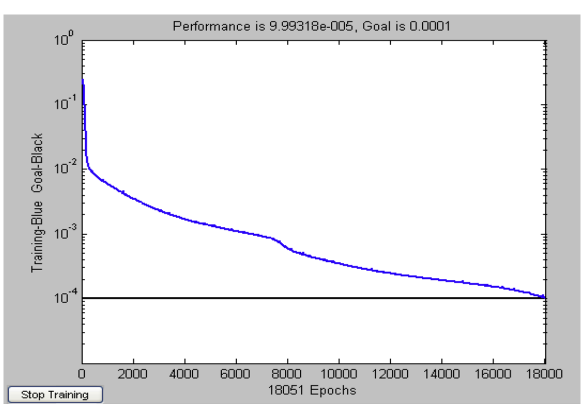

Fig. 3. Forecast error curve of network

From table 5, part of the prediction results by single-target method and comprehensive target method respectively are discrepant with the reality and they can't reflect the outburst risk degree. The reason is that those methods could not post the complicated relationship between influencing factors of coal and gas outburst. But the prediction results by BP nerve network are more accurate than others. So the method presented in the paper has certain practicability.

Table 4. Instances of coal and gas outburst of Yunan Enhong mine

Sample number	Initial velocity emission	Robustness coefficient	Gas pressure (MPa)	Destroy the type of coal	Mining depth /×102m	strength of outburst (t)
1	11	0.37	2.1	3	4.12	11
2	12.1	0.49	2.0	3	4.12	9
3	11.5	0.28	1.9	3	4.07	10
4	11.8	0.36	2.3	3	4.03	15
5	10.8	0.30	2.2	3	3.96	9
6	12.4	0.38	1.8	3	4.10	9.3
7	11.8	0.57	1.6	3	4.08	36.8
8	10.0	0.55	1.5	3	4.05	10.8

Table 5. Comparison of forecast results between grey-neural network and other forecast methods

Sample number	Initial velocity emission	Robustness coefficient	Gas pressure (MPa)	Destroy the type of coal	Mining depth /×102m	K	S	C	BP
1	11	0.37	2.1	3	4.79	20	you	you	Small
2	12.1	0.49	2.0	3	4.12	18.0	you	you	Small
3	11.5	0.28	1.9	3	1.4	16.8	you	you	Small
4	11.8	0.36	2.3	3	2.4	14.2	you	wu	Small
5	10.8	0.30	2.2	3	2.8	19.4	you	you	Small
6	12.4	0.38	1.8	3	4.7	17.5	you	you	Small
7	11.8	0.57	1.6	3	3.9	16.1	Wu	you	Small
8	10.0	0.55	1.5	3	1.8	20.5	wu	you	Small

Single-target method and comprehensive target method are respectively instead by S and C.

5. Conclusions

1) Seven main effect factors of coal and gas outburst are analyzed, and actual data in eight typical coal and gas outburst mines in China are collected. Through the Grey correlation analysis, we get the correlation order of effect factors affecting coal and gas outburst.

2) Neural network forecasting model of coal and gas outburst is built. According to the result of grey correlation analysis, Input Elements in Grey-neural Network Forecasting Model are determined.

3) 20 Chinese typical examples of coal and gas outburst are collected to train the network model. The trained gray- neural network model has been applied in Yunnan Enhong coal mine and then checked usefulness and accuracy, showing that the grey - neural network model is suitable for predicting coal and gas outburst.

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