Research on Early Warning Model of Coal and Gas Outburst Based on Multi-sensor Information Fusion

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Abstract

Coal and gas outburst is the most frequently occurred in our country, hurt one of the most serious mine disasters, strengthen the monitoring and early warning is an effective means of preventing coal and gas outburst accident, single sensor monitoring and early warning is can meet the actual coal mine complex environment.Based on the multi-sensor data fusion technology combined with the actual coal mine gas environment, based on the dynamic and static outburst prediction index comprehensive analysis, put forward a kind of based on multi-sensor information fusion model of coal and gas outburst early warning in different levels of the early warning model to choose effective information fusion algorithm to realize the coal and gas outburst early warning, and with the actual mine working face outburst prediction index data analysis, comprehensive analysis of the early warning model has carried on the preliminary application of multi-sensor information fusion technology to improve the reliability of coal and gas outburst early warning and intelligent level is of great significance.

Keywords

Coal and gas outburst, forewarning model, multi-information fusion, analytical hierarchy process.

1. Introduction

China is one of the countries most threatened by gas disasters in the world. It mainly focuses on coal and gas outburst disasters. Gas mine safety monitoring and disaster warning of strong coal mines are of great significance for effectively preventing coal and gas outbursts and reducing casualties. Since the early 1980s, when China introduced coal mine early warning systems from Poland, Germany, the United Kingdom and the United States[1,2], China's coal mine monitoring and early warning technology has made significant progress, and single sensor monitoring and warning has been unable to meet the complexity. The actual underground coal mine environment, the integration, intelligence, and networking of the early warning system has become a new development direction[3,4]. Multi-sensor data fusion technology can comprehensively analyze the information of different kinds of sensors (such as gas, temperature, wind speed,etc.), and provides a new way to improve the reliability and intelligence level of coal mine gas safety monitoring and disaster warning system[5].

At present, multi-sensor data fusion technology has also been applied and researched in the field of coal mine safety in China. Based on the research of different levels of data fusion structure in coal mine monitoring and early warning system, the literature[6,7] proposed a distributed data fusion

structure for coal mine monitoring and early warning system. In[8], the combination of multi-sensor arithmetic mean and batch estimation algorithm is used to conduct coal mine warning. Compared with the traditional method of using arithmetic mean, the results are more accurate and reliable. Literature [9] combines Bayesian estimation algorithm with adaptive weighting algorithm to realize the processing and analysis of coal mine gas and other indicators data, and then uses D-S evidence theory to optimize the index parameters to carry out early warning of coal mine gas environment. The literature[10,11] adopts the method of multi-sensor fuzzy information fusion, which is fuzzified by the relevant indicator parameter data in the coal mine, thus reducing the inaccuracy of relying on a single sensor for early warning. In[12], the method of combining rough set theory with neural network is adopted, and the obtained data is first processed by rough set theory. Then the processing results are processed by the neural network method, and finally the early warning of the coal mine safety environment is determined. In[13], a three-layer multi-sensor data fusion model is proposed. The data level is determined by AHP, and then the fuzzy theory and evidence theory are combined to make decision evaluation. However, the DS evidence theory is not improved at the decision-making level. . By combining multi-sensor data fusion technology with actual coal mine gas environment, this paper proposes a coal and gas outburst early warning model based on multi-sensor information fusion, and selects appropriate and effective information fusion algorithm to realize coal and gas outburst at different levels of early warning model. Early warning, thereby improving the level of coal mine gas warning and ensuring safe production in coal mines.

2. Analysis on indicators and factors of coal and gas outburst

2.1 Determination of coal and gas outburst prediction indicators

At present, the prediction of coal and gas outburst risk can be mainly divided into regional prediction and working surface prediction. Experts at home and abroad analyzed the influencing factors of coal and gas outburst from different angles, and proposed the critical values of various impact indicators and prominent sensitive indicators. According to the adopted forecasting methods, the influencing factors can be roughly divided into static indicators and dynamic indicators [14],15]. The static indicator method includes the single index method and the comprehensive index D and K methods. The comprehensive index method includes temperature index, electromagnetic radiation intensity index, elastic wave velocity index and gas emission dynamic index. The determination process of coal and gas outburst prediction index is shown in Figure 1. The index with larger weight is selected as the forecasting index to form the data processing fusion of different features of the feature layer, such as the comprehensive index D/K, gas emission initial velocity q, maximum drilling. The amount of scrap Smax is considered as an independent index, and other prominent indicators with less weight, such as roadway type, depth (exploitation depth), coal seam thickness, dip angle, geological structure, operation mode, etc., are used as neural network prediction methods. The input parameters are based on a highly nonlinear mapping relationship of the neural network to establish a coal and gas outburst prediction model. According to the selected factors of coal and gas outburst and corresponding indicators, appropriate measuring sensors are selected to accurately obtain the index parameter values.

2.2 Weight Analysis of Factors Affecting Coal and Gas Outburst

Through the analysis of the factors affecting coal and gas outburst, the analytic model of the factors affecting coal and gas outburst is established, and the weight sorting vector is obtained, which intuitively reflects the weight of each factor affecting coal and gas outburst, which will affect coal and The qualitative indicators of gas outburst are quantified, which is convenient for discriminant analysis and provides a scientific basis for predicting and preventing coal and gas outburst.

1) Selection factor set

Due to the many factors affecting coal and gas outburst, representative factors are selected for analysis. In this paper, the coal seam and gas outburst danger are evaluated by the coal seam depth H, coal seam thickness M, coal seam dip angle α, geological structure T, roadway type Y, initial velocity of

borehole gas emission *q*, comprehensive index *D/K*, operation mode *W*, and maximum amount of drill cutting during drilling *S*.

2) Constructing a judgment matrix

The judgment matrix is constructed by comparing the two factors, according to its importance to the prominent hazard, according to the scale shown above by the experienced technicians and experts, here select a high gas mine, which The judgment matrix of each influencing factor of coal and gas outburst is shown in Table 1.

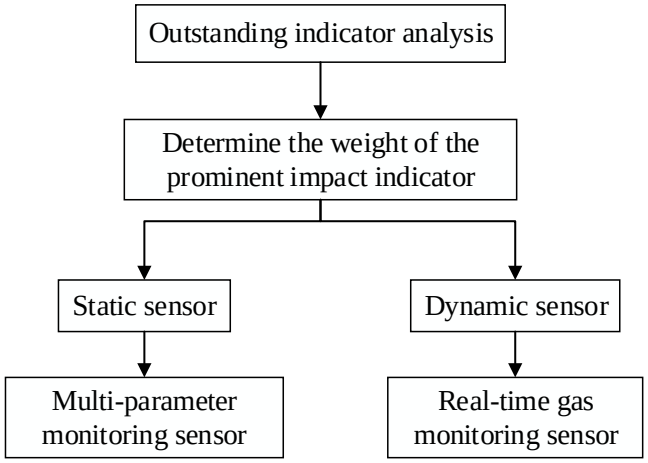

Fig.1 Determination of coal and gas outburst index

Table 1 Coal and gas outburst influence factor judgment matrix

B	H	M	α	T	Y	q	D/K	W	S
H	1	2	1	1/5	1/5	1/2	1/5	1	1/5
M	1/2	1	1/3	1/5	1/3	1/3	1/8	1/3	1/5
α	1	3	1	1/5	1/3	1	1/5	1/2	1/3
T	7	5	5	1	5	5	1/3	1/5	1
Y	5	2	3	1/4	1	1/3	1/5	4	1/5
q	3	3	1	1/3	3	1	1/3	2	1/4
D/K	5	7	4	3	5	3	1	7	2
W	1	3	2	6	1/4	1/2	1/7	1	3
S	6	5	4	1	6	5	1/2	1/3	1

3) Find the eigenvalues and eigenvectors of the judgment matrix

The eigenvalues $\lambda_{\max}$ and *W* eigenvectors can be calculated using the square root method in the analytic hierarchy process. The steps are as follows:

① Calculate the product of each row element of the judgment matrix M^i

$$M_i = \prod_{j=1}^{n} b_{ij}, i = 1, 2, \cdots n \tag{1}$$

② Calculate M^i the root of the root and normalize the vector $\bar{W} = \left[\bar{W}_1, \bar{W}_2, \cdots \bar{W}_n\right]$:

$$W_i = \frac{\bar{W}_i}{\sum_{j=1}^{n} \bar{W}_j} \tag{2}$$

③ Calculate the maximum eigenvalue of the judgment matrix $\lambda_{\max}$ =7.7835

Eigenvector W = {0.033 0.042 0.0564 0.373 0.12 0.212 0.369 .075 0.340}

4) Consistency test

According to the matrix consistency test method proposed above, the random consistency index RI is selected according to Table 1, and the consistency index CI=0.153, RI=1.42, CR=0.0918≤0.1 is obtained, which satisfies the consistency requirement, so the feature vector can be used. W is used as a weight vector.

5) Hierarchical weight vector sorting

The above-mentioned analysis of the factors affecting coal and gas outburst reveals that the judgment matrix meets the consistency requirements and has good consistency. Therefore, the eigenvector *W* obtained according to the above-mentioned steps can be used as the weight vector of the influence factors of coal and gas outburst. It can be seen that the weight of each factor is different, that is, the impact on the risk of coal and gas outburst. The degree is different. In order to more clearly characterize the size of the prominent factors, the weight vector *W* is sorted as shown in Table 2.

Table 2 Coal and gas outburst influence factor weight vector sort

Index	D/K	T	S	q	Y	W	α	H	M
Weight Coefficient	0.352	0.368	0.32	0.112	0.07	0.075	0.082	0.096	0.041

It can be seen from Table 2 that the weights affecting coal and gas outburst factors are from large to small: comprehensive index D/K, geological structure T, maximum cuttings index S, initial gas velocity of borehole gas q, roadway type Y , operation mode W, coal seam dip angle, coal seam depth H and coal seam thickness M, to fully consider the weight coefficient of these factors when predicting coal and gas outburst.

3. Multi-sensor information fusion coal and gas outburst prediction model

3.1 Predictive model establishment

According to the current coal mine gas outburst prevention rules and anti-surge monitoring methods, manual measurement data occupies the main part, and some non-main influencing factors of physical sensor measurement as reference indicators, such as wind speed, temperature and so on. Sensor information fusion coal and gas outburst prediction model proposed by monitoring sensor subsystem, feature level information fusion processing subsystem, information management and decision support subsystem (including information management, expression evaluation and decision support three layers of fusion) and sensor management system The composition, coal and gas outburst prediction cycle model. The computer obtains multi-category and heterogeneous sensor information in time series, and automatically analyzes and synthesizes it under certain criteria to complete the decision-making and information processing process required for coal and gas outburst conditions. The same and heterogeneous multi-sensors (including generalized sensors) and wide-area network environment systems are the hardware foundation of data fusion. Multi-source information is the processing object of data fusion. Coordination management and comprehensive processing are the core of data fusion.

3.2 Layered multi-sensor information fusion method

While analyzing the general algorithm of multi-sensor information fusion and the fusion methods of each level, the deep neural network is selected as the feature layer multi-sensor fusion method, and the traditional BP neural network is improved. The back propagation algorithm based on unsupervised learning is used. The automatic encoder performs information recognition. Considering the inherent shortcomings of neural networks, D-S evidence theory is proposed as a decision-level fusion method, which constitutes a hierarchical fusion structure of feature level and decision level, which increases the reliability of decision-making.

4. Work surface highlights forecasting indicator application

4.1 Mine working surface highlighting forecast data

This paper predicts and analyzes the drill cuttings gas analysis index Δh2, the initial gas velocity q of the borehole gas and the cuttings amount S of the drilling hole predicted by the mining face of a mine 11031. Select the outstanding predictive indicators within a period of 01~30 days to track the survey values for analysis. as shown in Table 3.

Table 3 Table of working face highlights the indicator monitoring

Date	Δh2	q	S	Date	Δh2	q	S
3.1	40	1.27	1.6	3.16	40	0.41	2.4
3.2	80	0.87	2.4	3.17	40	0.87	2.2
3.3	80	0.86	1.8	3.18	40	0.87	2.2
3.4	40	0.77	2.6	3.19	80	1.13	2.4
3.5	60	0.92	2.6	3.20	40	1.16	2.2
3.6	60	0.92	2.6	3.21	80	1.13	2.2
3.7	60	1.05	2.4	3.22	60	1.01	2.2
3.8	80	0.92	2.4	3.23	60	0.92	2.4
3.9	60	0.82	2.4	3.24	40	0.71	2.6
3.10	40	0.87	2.4	3.25	60	0.68	2.6
3.11	60	0.92	2.4	3.26	40	0.41	2.4
3.12	40	0.87	2.2	3.27	60	0.92	2.2
3.13	40	1.59	2.4	3.28	60	0.96	2.4
3.14	60	0.87	2.4	3.29	60	0.69	2.2
3.15	60	1.09	2.4	3.30	60	0.5	2.4

4.2 Outstanding indicator prediction analysis

This The autoregressive moving average model ARMA(p,q) is the most widely used stationary sequence fitting model. It can be subdivided into AR(p), MA(q), and ARMA(p,q). Corresponding to this is the summation autoregressive moving average model ARIMA(p,d,q), which is very suitable for non-stationary time series fitting models. The autoregressive model is the simplest ARMA model, which is a model that uses different post-terms of time series $\{Y_t\}$ as explanatory variables. The model form is as follows:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \tag{3}$$

Where: ϕ_1, ϕ_2, …, ϕ_p is the regression coefficient; e_t is the normal distribution white noise with mean 0, δ_e^2 is variance; p is the regression order, which is the number of explanatory variables in the model. Equation (1) p is called a step autoregressive model.

There are many parameter estimation methods for AR(p) model. In this paper, the least squares method is used to estimate the known sample sequences X1, X2, ..., Xn, and the formula (7-3) is written in matrix form.

$$y = -X\vartheta + e \tag{4}$$

$$y = \begin{Bmatrix} x_p + 1 \\ x_p + 2 \\ \vdots \\ x_m \end{Bmatrix}, \vartheta = \begin{Bmatrix} \vartheta_1 \\ \vartheta_2 \\ \vdots \\ \vartheta_p \end{Bmatrix}, e = \begin{Bmatrix} e_{p+1} \\ e_{p+2} \\ \vdots \\ e_m \end{Bmatrix} \tag{5}$$

$$\vartheta = (X^{'}X)^{-1}X^{'}y \tag{6}$$

$$\vartheta = \frac{1}{m-p}S(\vartheta) = \frac{1}{m-p^{p+1}}e(n)^2 \tag{7}$$

Forecast future data and calculate relative error and average error rate:

$$X = \frac{q_s - q_r}{q_r} * 100\% \tag{8}$$

In the formula, the relative error is X expressed, and the average value is the error average rate; q_s is a statistical value; q_r is a statistical prediction value.

The Levinson function in the signal processing in the Matlab toolbox is used to simulate the AR model so that the order p=0 starts to increase sequentially. When the AR(p) model is consistent with the original sequence, the simulation requirements are met and the value of p is determined. When the order is 3, the simulation sequence which is consistent with the original sequence can be simulated, that is, the parameters of the AR(3) model are relatively accurate. From the formulas (7) and (8), the minimum autoregressive coefficients using Matlab are 1.0000, respectively. -0.9706, 0.0304, 0.0229. According to the prediction formula of AR(3):

$$y_t = y_t - 1 + 0.9706y_{t-2} + 0.0304y_{t-3} + 0.0229 \tag{9}$$

It is concluded that y16=38.89, y17=38.25, y18=39.54, and the average error rate is 4.3%, which shows that the predicted gas emission is relatively reliable.

5. Conclusion

Based on the data flow characteristics of coal mine monitoring system, this paper determines the fusion level of gas data and constructs a gas warning model based on data fusion of multiple sensors. The main conclusions are as follows:

1) Based on the multi-parameter monitoring and analysis of dynamic and static sensors, the analytic hierarchy process is used to calculate the weight of the prominent impact indicators, and then the outstanding predictive indicators are determined.

2) Sensor information fusion coal and gas outburst prediction model consists of monitoring sensor subsystem, feature level information fusion processing subsystem, information management and decision support subsystem and sensor management system, using multi-layer multi-sensor fusion method for analysis and calculation, prediction The warning results are more reliable.

3) Using the autoregressive moving average model to analyze the outburst prediction index of a mine face shows that the gas emission amount is more reliable than the drill cutting gas analysis and the cuttings amount index.

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