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Prediction of coal and gas outburst risk at driving working face based on Bayes discriminant analysis model

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Abstract. With the coal mining depth increasing, both stress and gas pressure rapidly enhance, causing coal and gas outburst risk to become more complex and severe. The conventional method for prediction of coal and gas outburst adopts one prediction index and corresponding critical value to forecast and cannot reflect all the factors impacting coal and gas outburst, thus it is characteristic of false and missing forecasts and poor accuracy. For the reason, based on analyses of both the prediction indicators and the factors impacting coal and gas outburst at the test site, this work carefully selected 6 prediction indicators such as the index of gas desorption from drill cuttings Δh_2, the amount of drill cuttings S, gas content W, the gas initial diffusion velocity index ΔP, the intensity of electromagnetic radiation E and its number of pulse N, constructed the Bayes discriminant analysis (BDA) index system, studied the BDA-based multi-index comprehensive model for forecast of coal and gas outburst risk, and used the established discriminant model to conduct coal and gas outburst prediction. Results showed that the BDA - based multi-index comprehensive model for prediction of coal and gas outburst has an 100% of prediction accuracy, without wrong and omitted predictions, can also accurately forecast the outburst risk even for the low indicators outburst. The prediction method set up by this study has a broad application prospect in the prediction of coal and gas outburst risk.

Keywords: coal and gas outburst; prediction; working face; Bayes discriminant analysis

1. Introduction

Coal has been in the dominant position of energy consumption in China. Even though proportion in the total primary energy consumption gradually lowers in recent years, it always remains above 60%. The geological conditions of coal mining in China are very complicated, coal and gas outburst occur very frequently and more seriously. According to statistics, about one third of coal and gas outburst accidents totaled in the world occurred in China. Thus, this kind of accidents has become one of the major safety problems faced by Chinese coal mining industry (Xu *et al.* 2006, Skoczylas, 2012). Currently, Chinese coal mining is deepening at average of 8-12 m/a, even at 10-25 m/a some key state-owned coal mines and the mining depth of some coal mine wells has risen to 1000 m. With coal mining depth increasing annually, many shallow non-outburst coalbeds turn to deep outburst-prone coalbeds. In addition, increase in mining depth is accompanied with increases in stress, gas pressure and gas content, as well as decrease in coal permeability, all of which makes coal and gas outburst risk become increasingly complex and serious (Chen *et al.* 2018).

The conventional method for prediction of coal and gas outburst risk is to measure the gas initial diffusion velocity index from boreholes, the weight of drill cuttings, and the like by drilling at the working face and based on their critical values to forecast the risk of outbursts risk at the face. However, the conventional indexes are obtained through a large number of engineering practice verification, and their critical values are also deduced by a lot of experiences on outburst accidents. Obviously, the method is often unable to predict outburst with low indexes. Thus, researchers have proposed a variety of prediction methods for coal and gas outburst. To name a few, the method of gas peak-to-valley ratio (Li and Zhou 2012), the method of methane concentration and V_{30} (Toraño *et al.* 2012), the method of coal desorption property V_1 (Fernandez-diaz *et al.* 2013), the method of gas expansion energy (Jiang *et al.* 2014), came consecutively in view. Meantime, the typical geophysical methods, such as microseismic method (Lu *et al.* 2012), fine detection technology (Wang *et al.* 2019), and acoustic emission method (Lu *et al.* 2014), advanced rapidly and achieved on-line monitoring of coal and gas outburst.

However, using a single index for prediction is difficult to reflect the effects of various impacting factors on coal and gas outburst and makes inaccurate and missing predictions frequently appear (Li *et al.* 2015). It is clear that through multi-index prediction and comprehensive determination for the outburst risk may compensate for the disadvantages of the single index method and improve the

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prediction accuracy. Thus, researchers conduct their various beneficial attempts. Some researchers designed a gas-measurement-tube to measure gas pressure and its changes at outburst-prone regions, calculated the permeability of coalbeds nearby the working face, and based on which further evaluated the risk of coal and gas outburst (Aguado and Nicieza 2007). And underground horizontal boreholes were utilized to test the permeability and stress, the strength and adsorption properties of sampled coal were measured in their laboratory, and based on which adopted Monte Carlo technique to assess the risk of outbursts (Wold *et al.* 2008).

In addition, a comprehensive evaluation system was proposed, using indexes including gas content, gas pressure, etc., to predict the risk of coal and gas outburst in coal mines based on catastrophe theory (Zhang *et al.* 2009). An artificial neural network and SVM were used to predict coal and gas outburst (Chen *et al.* 2014, Cheng *et al.* 2015, Zhang and Lowndes 2010); a gray target model was established with consideration of gas pressure, destructive type of coal, coal rigidity, coal rigidity, and initial speed of methane diffusion, the four factors influencing coal and gas outburst, based on the gray system theory to predict coal and gas outburst (Hu *et al.* 2015). A Fisher discriminant analysis index system using the gas adsorption index of drilling cutting Δh_2, the drilling cutting weight S, the initial velocity of gas emission from borehole q, the thickness of soft coal h, and the maximum ratio of post-blasting gas emission peak to pre-blasting gas emission $B_{\max}$ was constructed, and an FDA-based multiple indicators discriminant model was applied to predict coal and gas outburst (Chen *et al.* 2017).

Although these methods have achieved many good results, they are not broadly applied in the prediction of coal and gas outburst due to their poor accuracy, slower computational speed, or others. Thus, it is necessary finding such a method with both prediction accuracy and on-site applicability for the forecast of coal and gas outburst. The Bayes discriminant analysis (BDA) derived from the linear discriminant analysis (LDA) can be used to distinguish new samples and classify them into known groups. The BDA has been successfully applied to identify the stability of complicated goaf (Hu and Li 2012), to predict the risk of debris flow in coal mine (Xu *et al.* 2013), and to classify the spontaneous combustion tendency of sulfide minerals in metal mines (Luo *et al.* 2014). This work tried to use the BDA to set up the multi-index discriminant model for coal and gas outburst prediction and applied the model to forecast the outburst risk on the site to apply it.

2. Bayes discriminant analysis

Given a total of g m-dimensional groups G_1, G_2, ⋯, and G_g, they correspond to mutually different, m-dimensional probability density functions $f_1(X)$, $f_2(X)$, ⋯, and $f_g(X)$, respectively, each group, G_i, consists of all the values of the index $X = (X_1, X_2, \ldots, X_m)^T$ belonging to it. In practical applications, it is necessary for discriminant analysis to extract the data of every group in the training samples so as to construct certain criteria to determine the ownership of new samples. The BDA is divided into the BDA with two normal populations and the BDA with multiple normal populations. The research objects in this work are both outburst and non-outburst of the working face, thus only the BDA with two normal populations is introduced as follows (Zheng *et al.* 2009):

2.1 Introduction to the method

2.1.1 Mahalanobis distance and discriminant function

Suppose that G is an m-dimensional population with its mathematical expectation value μ and covariance matrix Σ, its Mahalanobis distance between the m-dimensional sample X and the population G is defined as

$$d(X,G)\underline{\Delta}[(X-\mu)^T\Sigma^{-1}(X-\mu_i)]^{\frac{1}{2}} \tag{1}$$

Suppose that 2 different m-dimensional populations G_1 and G_2 with their corresponding mathematical expectation values μ_1 and μ_2 and corresponding covariance matrices Σ_1 and Σ_2. The difference of square of Mahalanobis distances from the sample X separately to these two populations is

$$d^2(X,G_2)-d^2(X,G_1)=2[X-\frac{1}{2}(\mu_1+\mu_2)]^T\Sigma^{-1}(\mu_1-\mu_2) \tag{2}$$

Let $W_{(x)}$ be the discriminant function and equal to

$$W_{(X)}=[X-\frac{1}{2}(\mu_1+\mu_2)]^T\Sigma^{-1}(\mu_1-\mu_2) \tag{3}$$

2.1.2 Bayes discriminant function

Let 2 m-dimensional populations G_1 and G_2, whose probability density function is

$$f_{i(X)}=(2\pi)^{-\frac{m}{2}}|\Sigma_i|^{-\frac{1}{2}}\exp\left[-\frac{1}{2}(X-\mu_i)^T\Sigma_i^{-1}(X-\mu_i)\right] \tag{4}$$

where μ_i and Σ_i respectively are the mean vector and the covariance matrix corresponding to two populations; $|\Sigma_i|$ is the determinant of Σ_i; i =1 and 2.

Suppose that Σ_1=Σ_2=Σ, from Eq. (2) and Eq. (3), we can find

$$\frac{f_{1(X)}}{f_{2(X)}}=\exp\left\{\frac{1}{2}[(X-\mu_2)^T\Sigma^{-1}(X-\mu_2)-(X-\mu_1)^T\Sigma^{-1}(X-\mu_1)]\right\}=\exp\{W_{(X)}\} \tag{5}$$

with its corresponding Bayes discriminant function

$$W_{(X)}=\left[X-\frac{1}{2}(\mu_1+\mu_2)\right]^T\Sigma^{-1}(\mu_1-\mu_2) \tag{6}$$

In the actual applications, if μ_1, μ_2 and Σ are unknown, they are estimated by training the sample, that is, substituting $\hat{\mu}_1=\overline{X}^{(1)}$, $\hat{\mu}_2=\overline{X}^{(2)}$ and Σ for μ_1, μ_2 and Σ in Eq. (6), respectively. Meanwhile

$$\hat{\mu}_k=\frac{1}{n_k}\sum_{i=1}^{n_k}X_i^{(k)}=\overline{X}^{(i)},\quad \hat{\Sigma}\underline{\Delta}\frac{(n_1-1)S_1+(n_2-1)S_2}{n_1+n_2-2} \tag{7}$$

$$S_k=\frac{1}{n_k-1}\sum_{i=1}^{n_k}(X_i^{(k)}-\overline{X}^{(k)})(X_i^{(k)}-\overline{X}^{(k)})^T;\quad k=1,2 \tag{8}$$

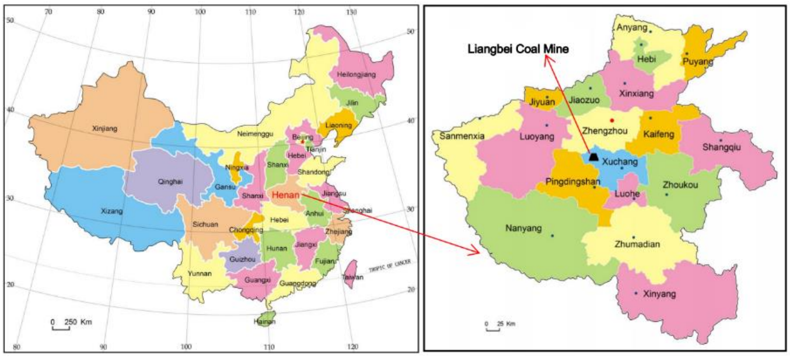

Fig. 1 Geographical location of Liangbei Coal Mine

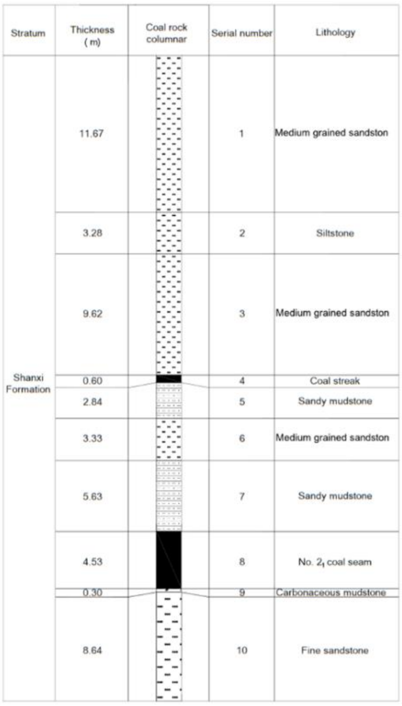

Fig. 2 Comprehensive stratigraphic column of the Shanxi Formation strata (with a scale of 1:200)

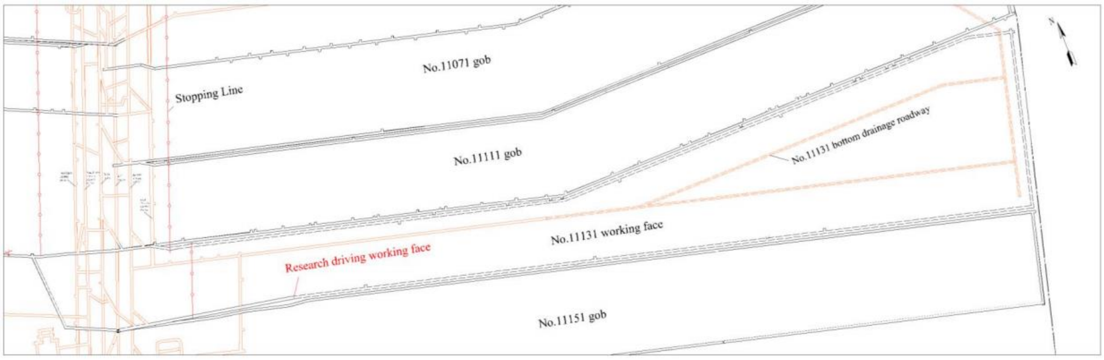

Fig. 3 Position of the work face for experiments

2.2 Bayes discriminant criterion and prediction

Let the prior probability distributions of G_1 and G_2 respectively be q_1 and q_2, their corresponding misjudgment losses are $c(2|1)$ and $c(1|2)$. For the specific sample X, the values of probability density functions of two populations at X are calculated with their Bayes criteria

$$\begin{cases} W_{(X)} \geq \ln \dfrac{q_2 c(1/2)}{q_2 c(2/1)}, & x \in G_1 \\ W_{(X)} < \ln \dfrac{q_2 c(1/2)}{q_2 c(2/1)}, & x \in G_2 \end{cases} \tag{9}$$

After determination of the discriminant criteria, the cross-validation based on training samples is applied to calculate the misjudgment rate, the procedure is:

1) Remove one sample from the training samples of G_1 (capacity n_1), then use both the remaining samples with capacity being n_1-1 and the samples of G_2 with capacity being n_2 to construct the discriminant function.

2) Use the constructed discriminant function to perform discriminant analysis of the removed sample.

3) Repeat steps 1) and 2) to remove all the training samples of G_1, let the number of misjudged samples be n_{12} *.

4) Repeat steps 1), 2) and 3) for the training samples of G_2, let the number of misjudged samples be n_{21} *, and define the following expression of r as the estimation of the misjudgment rate

$$r = \frac{n_{12}*+n_{21}*}{n_1+n_2} \tag{10}$$

3. Overview of the experimental site

The Liangbei Coal Mine is located at 37 km west of Xuchang City, Henan Province, China, as shown in Fig. 1. It belongs to Shenhuo Coal Industry Group. Its annual raw coal output is 900,000 tons. In its production process, the coal mine experienced many coal and gas outburst, extrusion, rib spalling, floor heave, and serious deformation of roof and both sides of roadway.

3.1 Coal seam

Currently, the main coalbed of Liangbei Coal Mine is No. 2_1 coalbed located at the bottom of the Permian Shanxi Formation. Fig. 2 shows comprehensive stratigraphic column of the Shanxi Formation at the scale of 1:200.

The experimental site is No. 11131 driving working face, as shown in Fig. 3. No. 11131 driving working face lies in the eastern No. 11 mining area. The north is No. 11111 gob and the south is No. 11151 gob, it results in No. 11131 as an island face. The No. 21 coalbed is characteristic of stable occurrence, relatively simple geological structure, and average thickness of 4.53 m, and the average dip of 13° in the range of 8~15°. Its immediate roof is a 5.63 m thick dark gray sandy mudstone with the well-developed horizontal bedding containing small visible Muscovite flakes and rich plant fossils debris. Its main roof is 3.33 m thick, gray, medium and grained sandstone composed of dominant quartz and minor feldspar and black minerals, and contains a large amount of carbonaceous and Muscovite chips and cemented siliceous mud. Its immediate floor is 8.64 m thick, dark gray, thin-layered, fine sandstone mixed with muddy strips with wavy bedding, and contains a large number of plant fossils fragments. Its main floor is 0.3 m thick carbonaceous mudstone.

Both the original gas pressure and the gas content of the coalbed are 0.6~3.65 MPa and about 5.73~13.97 m3/t, respectively. The attenuation coefficient of gas flow from borehole per 100 m into the coalbed is 0.0313~0.2588 d^{-1}, the gas permeability is 0.0011~0.0454 $m^2/MPa^2{\cdot}d$, so the coalbed is more difficult for gas drainage. The quality of coal is softer with the Protodyakonov coefficient of 0.15~0.25. The gas initial diffusion velocity index ΔP is 24~34.

3.2 Overview of coal and gas outburst

Several coal and gas outburst events occurred in the Liangbei Coal Mine. For example, on June 29, 1999, coal and gas outburst occurred during main crosscut excavation, discharging 180 tons of coal and 18,000 m^3 of gas; on July 8, 2009, coal and gas outburst happened during opening the No.2_1 coal seam at the return airway crosscut, ejecting 600 tons of coal and approximately 50,000 m^3 of gas. However, these two accidents didn't issue their casualties (http://www.chinasafety.gov.cn/gdaq/aqgd82.htm). Additionally, in the adjacent mine named Pingyu Coal Mine occurred two coal and gas outburst accidents on August 1, 2008 and October 16, 2010, respectively, 37 and 23 workers were killed (http://news.workercn.cn/c/2011/07/05/110705021110046559794.html). All these accidents show that Liangbei Coal Mine faces the great challenge against coal and gas outburst.

Meanwhile, the Liangbei Coal Mine also underwent many coal and gas outburst accidents with low indexes or dynamic phenomenon events, such as at 5:35 of September 11, 2012 the outburst occurred, discharging about 140 t of coal and approximately 15500 m^3 of gas. And for a long time before the accident, all the conventional indicators were detected normal. Fortunately, workers timely evacuated prior to its outburst due to the abnormal emission of gas. Thus, it is very difficult to forecast coal and gas outburst only relying on the traditional drilling method.

According to the outburst factors analysis of Liangbei Coal Mine, its gas initial diffusion velocity index ΔP is higher, thus, it is prone to outbursts with gas as the dominant outburst factor (Chao *et al.* 2015). Many dynamic events in coal mine are caused by the instability of coal–rock body (Liu *et al.* 2015). The Protodyakonov coefficient f as the representative of coal structure property is smaller, the capability of coal to resist external pressure is lower; the gas permeability is poor, and the resistance to gas flow is big, all of which also are other reasons causing coal and gas outburst (Liu *et al.* 2019). Therefore, in addition to relying on the traditional way of drilling, to accurately forecast coal and gas outburst at the Liangbei Coal Mine, it is still necessary to consider the gas content W, the gas initial diffusion velocity index ΔP, as well as other indicators which are more sensitive to the changes in stress, coal structure, and the like.

4. Prediction index system

According to BDA, first it is needed to determine the indicators for coal and gas outburst prediction. The outburst risk prediction indicators commonly used at working faces of coal mines in China mainly include the conventional borehole indicators and auxiliary indicators. Conventional

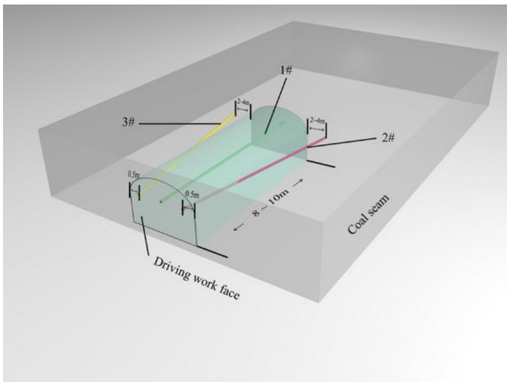

Fig. 4 Schematic of layout of boreholes for indexes testing

Fig. 5 KBD 5 coal and gas outburst electromagnetic radiation monitor

borehole indicators mainly include the gas initial diffusion velocity index from boreholes q, the drill cuttings S, the drill cuttings desorption Indexes K_1 and Δh_2, and the like; while auxiliary indicators involve the dynamic change in gas emission amount, gas content, electromagnetic radiation from coal rock, and others at the working face, as well as the geological conditions in the front of face obtained by drilling and other means.

No.11131 working face of Liangbei Coal Mine mainly uses the drill cuttings gas desorption index Δh_2 and the drill cuttings weight S to predict coal and gas outburst. Through above analysis of coal and gas outburst accidents occurring at the Liangbei Coal Mine, it is known that conventional indicators cannot meet the needs for accurately forecasting coal and gas outburst, while the gas content W and the gas initial diffusion velocity index ΔP can be used as predictors. In addition, the EMR-based technique for coal and gas outburst prediction was applied in the Jiaozuo Mining Area that belongs to the same coalbed with Liangbei Coal Mine, and proved that it has a good application prospect (Wang *et al.* 2011). And the EMR-based prediction technique was also proven to be more sensitive to the changes in stress and coal structure (Kong *et al.* 2019), thus, the EMR intensity E and number of pulse N were selected as the predictors for coal and gas outburst at the Liangbei Coal Mine. Physical meanings of various predictors in the prediction index system are described as follows.

4.1 Gas initial diffusion velocity index ΔP

The gas initial diffusion velocity index in China is one of the main indicators used to identify the outburst-prone coal seam. It is defined as the difference between the accumulated gas emitted into the space of fixed volume at 60 s and 10 s from coal samples of definite size and quality under the pressure of 0.1 MPa. The larger the ΔP value is, the greater the gas initial diffusion velocity index, the more serious the degree of damage to coal, the higher the possibility of the coal and gas outburst. The critical ΔP value is 10.

4.2 Borehole indexes

As using the borehole indicator method to predict outburst risk at the face, at least 3 boreholes of 42 mm in diameter and 8~10 m in depth should be bored from face to proper position deep into the coalbed. They should be arranged as far as possible in the soft stratum: one in the middle of the face and parallel to the driving direction, the orifices of the remaining two at the positions 0.5 m far from the two ribs of the roadway with bottom points at the positions 2~4 m outside the outlines on both sides of the roadway, as shown in Fig. 4. In order to determine the drill cuttings weight S and the gas desorption index Δh_2, each time drilling 1 m deep into the coalbed, collecting the drill cuttings of 1~3 mm in size discharged at the orifice, and measuring the drill cuttings weight S. Gas desorption index Δh_2 should be measured at least once for every 2 m drilling into the coalbed.

4.2.1 Drill cuttings weight S

The indicator jointly considers the main factors determining outburst risk as the stress, gas pressure, and coal's physical and mechanical properties. The larger the index value, the greater the risk of coal and gas outburst. The critical value outburst occurs is 6 kg/m.

4.2.2 Index of gas desorption from drill cuttings Δh_2

The indicator jointly reflects two outburst-risk related factors, coal's degree of damage and gas pressure. The larger the indicator value is the higher the coal's damage degree, the greater the gas pressure and the stronger the coal and gas outburst risk. The critical value outburst occurs is 200 Pa.

4.3 Gas content W

The determination of gas content W depends upon the measurements of all its related physical quantities, namely, the volume of gas desorption from underground coal samples, volume of lost gas, volumes of pre- and post-failure natural desorption gas, and volume of in-desorbed gas. Gas pressure has a significant effect on the development process of gassy coal extrusion (Sa *et al.* 2019). According to the national regulation, the region where the gas pressure is less than 0.74 MPa or the gas content is less than 8 m^3/t can be regarded as areas without risk of coal and gas outburst. In Henan province where Liangbei Coal Mine is located, the regulation is stricter as

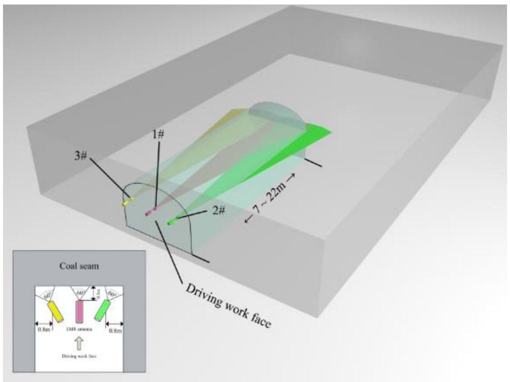

Fig. 6 Arrangement schematic of EMR measuring points

the regions with gas pressure less than 0.6 MPa or gas content less than 6 m^3/t is considered to be no coal and gas outburst risk. Thus, the critical value of gas content W is 6 m^3/t.

4.4 EMR intensity E and the number of pulse N

Coal rock EMR is released from coal rock as it deforms and fails under a certain stress. Its change reflects the state of coal rock and the process of its damage under a certain external pressure. The instrument for in-situ testing is KBD 5 coal and gas outburst electromagnetic radiation monitor developed by China University of Mining and Technology, as shown in Fig. 5.

This device includes a high sensitivity broadband directional antenna, monitoring host, charger and data processing software. The main technical parameters and characteristics of KBD 5 monitor are (1) directional receiving electromagnetic radiation signals, (2) automatically data acquisition and storage, (3) effective monitoring direction: 60°, (4) effective monitoring depth: 7~22 m, (5) frequency bandwidth: 1~500 kHz, (6) communication method: computer serial communication, and (7) intrinsically safe for coal mine. The data tested by electromagnetic radiation monitor are EMR intensity and EMR pulse.

The testing procedure of KBD 5 EMR monitor is: Coal and gas outburst occurring→Coal and rock's violent deformation and fracture→Generating EMR signals→ Directional antenna→EMR monitor→RS 232 port→Computer→Data processing software→display and forecasting (He *et al.* 2012).

The EMR-testing process includes 1) place the EMR receiving antenna facing the front, and 2) set three testing points at the left, middle, right of the heading face, among them, the middle one is 0.5 m away from the front face, while the left and right ones are 0.8 m from the bilateral roadways, as shown in Fig. 6 (Li *et al.* 2015).

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According to preliminary testing and critical value setting methods (Wang *et al.* 2011), the critical values of EMR intensity E and its number of pulse N are 75 mV and 195 Hz, respectively.

5. BDA-based model and its application

A BDA model is established based on multiple sets of actually measured data and Bayes basic discriminant principles for prediction of coal and gas outburst and applied on the field.

5.1 BDA model for coal and gas outburst

The risk of coal and gas outburst at the face is determined following the criterion that whether the predictors exceed their critical values or occurrence of dynamic phenomena as gas spurt from drilling, etc. Presence and absence of outburst risk are marked by 'Y' and 'N', respectively. These two classes are used as BDA's two normal populations G_1 and G_2 to establish the discriminant model for prediction of face coal and gas outburst risk at the face.

Table 1 shows a total of 50 sets of data measured from the No.11131 driving working face of Liangbei Coal Mine in accordance with the above-mentioned prediction index system consisting of the drill cuttings amount S, drill cuttings gas desorption index Δh_2, gas content W, the gas initial diffusion velocity index ΔP, EMR intensity E and its number of pulse N. Based on the index system and actually measured data, the established BDA discriminant models are described as follows

$$\begin{aligned} W_1 &= 13.971*S+0.296*\Delta h_2+0.775*W+7.369*\Delta P+0.077*E\text{-}0.021*N-105.307 \\ W_2 &= 9.579*S+0.193*\Delta h_2+1.848*W+4.342*\Delta P+0.042*E\text{-}0.021*N-45.497 \end{aligned} \quad (11)$$

where W_1 and W_2 denote the discriminant function values in the presence and absence of outburst risk, respectively.

The misjudgment rate is calculated using the cross-validation estimation method based on training samples. Table 1 lists the calculated or predicted results. From the table, it is clear that all the prediction results are correct. Thus, the established discriminant model has stable and accurate discriminating capability.

Table 1 Outburst risk prediction indexes and backward substitution check-up of discriminant results

Group	Drilling cutting weight S/kg.m^{-1}	Gas adsorption index of drilling cutting Δh_2/Pa	Gas content W / m^3.t^{-1}	Initial speed of gas emission $\triangle P$	EMR intensity E/mv	EMR pulse N/Hz	Actual risk	Outburst risk discriminant function value W_1	Outburst risk discriminant function value W_2	Forecast risk (Y/N)
1	4.2	140	3.60	14	74	220	Y	101.85	87.68	Y
2	3.4	120	4.40	7	34	141	N	32.37	47.23	N
3	3.1	100	2.67	7	48	80	N	23.27	39.17	N
4	3.4	80	2.49	4	44	140	N	-2.27	23.39	N
5	4.1	120	2.58	5	28	78	N	26.85	42.95	N
6	4.2	120	3.20	4	34	42	N	22.58	41.72	N
7	4.4	100	4.50	6	55	80	N	36.02	50.95	N
8	4.1	120	4.10	7	42	72	N	43.98	55.16	N
9	3.2	100	2.67	6	23	49	N	16.03	35.39	N
10	3.3	160	2.59	6	11	36	N	34.47	47.54	N
11	2.8	80	2.73	5	17	78	N	-3.87	22.60	N
12	5.2	180	3.07	11	125	188	Y	109.72	93.78	Y
13	5.7	140	3.73	6	62	152	N	64.45	68.47	N
14	4.0	140	6.60	7	121	550	Y	46.48	55.96	Y
15	2.6	120	3.80	6	45	80	N	15.48	35.85	N
16	3.2	160	3.50	6	67	157	N	35.58	48.09	N
17	4.1	90	2.34	5	48	110	N	18.66	36.89	N
18	4.0	240	6.20	14	93	1031	Y	115.06	93.62	Y
19	3.2	140	3.61	7	52	160	N	35.86	48.07	N
20	2.7	140	2.44	5	37	28	N	14.85	34.57	N
21	3.3	160	5.20	8	55	24	N	54.87	63.15	N
22	3.8	100	2.57	6	60	165	N	24.78	40.08	N
23	6.8	140	6.10	8	73	440	Y	91.20	86.50	Y
24	3.0	120	4.34	8	43	95	N	35.76	48.97	N
25	4.1	80	2.99	6	46	34	N	25.02	42.02	N
26	2.6	60	3.44	8	62	51	N	14.10	33.62	N
27	3.0	120	4.20	7	58	160	N	28.07	43.63	N
28	3.6	120	3.80	5	48	223	N	19.31	38.21	N
29	3.8	120	3.90	7	39	45	N	39.97	52.36	N
30	3.4	100	3.00	7	26	66	N	26.32	42.02	N
31	4.7	220	5.50	11	53	213	Y	110.36	97.64	Y
32	4.4	130	4.60	5	34	141	N	34.70	50.41	N
33	3.2	120	4.10	7	32	112	N	29.79	45.28	N
34	4.0	100	2.72	6	56	60	N	29.56	44.29	N
35	3.2	150	2.26	7	41	75	N	35.03	46.65	N
36	4.1	130	2.62	7	55	97	N	42.58	52.20	N
37	3.1	190	2.53	6	52	77	N	42.82	52.17	N
38	3.7	170	5.10	7	42	72	N	53.96	62.83	N
39	6.6	170	2.75	9	193	289	Y	114.43	96.72	Y
40	4.0	150	2.34	7	25	66	N	48.91	56.15	N
41	4.2	110	5.00	14	58	47	Y	96.45	87.44	Y
42	5.0	110	3.20	16	71	54	Y	121.83	100.86	Y
43	3.9	110	3.01	6	49	34	N	31.35	46.06	N
44	4.8	220	2.54	10	52	110	Y	104.23	90.93	Y
45	3.0	110	2.50	8	21	18	N	31.26	44.31	N
46	2.9	120	2.45	6	48	14	N	20.22	37.73	N
47	3.0	100	2.87	6	63	133	N	14.72	33.76	N
48	2.8	110	3.80	7	76	232	N	21.84	38.27	N
49	3.9	230	3.14	8	61	55	Y	78.50	76.02	Y

Table 2 Forecast results

Group	Drilling cutting weight S/kg.m^{-1}	Gas adsorption index of drilling cutting Δh_2/Pa	Gas content W /m^3.t^{-1}	Initial speed of gas emission ΔP	EMR intensity E/mv	EMR pulse N/Hz	Actual risk	Outburst risk discriminant function value W_1	No outburst risk discriminant function value W_2	Forecast risk
1	3.6	120	2.67	8	37	143	N	37.69	48.21	N
2	2.6	150	2.44	6	39	123	N	21.94	37.97	N
3	2.6	130	2.34	7	38	29	N	25.18	40.18	N
4	3.0	110	2.30	8	42	155	N	29.88	41.96	N
5	4.2	160	3.23	9	47	68	Y	71.75	71.21	Y
6	3.8	110	4.23	12	103	93	Y	78.00	74.41	Y
7	4.8	110	3.10	13	55	121	Y	94.21	83.66	Y
8	4.4	180	2.73	8	43	131	Y	71.07	70.22	Y
9	4.6	220	4.80	8	47	53	Y	89.26	85.49	Y
10	3.0	150	2.93	9	31	92	N	50.05	56.05	N
11	2.4	150	2.26	7	51	77	N	24.58	39.37	N
12	4.2	130	2.65	13	65	62	Y	93.40	82.60	Y
13	5.1	110	3.10	12	55	232	Y	88.70	79.86	Y
14	4.8	110	2.30	11	62	19	Y	81.53	75.92	Y
15	3.6	110	2.20	8	44	86	N	39.79	49.06	N
16	3.1	110	3.01	7	38	91	N	25.50	41.08	N
17	3.5	130	2.34	7	43	58	N	37.56	48.42	N
18	3.2	130	2.50	7	52	116	N	29.29	42.84	N
19	4.1	230	6.20	8	50	156	Y	84.39	83.18	Y
20	5.0	180	5.00	8	33	208	Y	78.83	78.13	Y

5.2 Application of BDA model

The discriminant model, namely Eq. (11) is applied to predict of the outburst risk of 20 sets of newly tested data according to the above Bayes criterion. Table 2 shows the results. In accordance with the principle that higher than the borehole index critical value or dynamic phenomena such as gas spurt from borehole, etc. are regarded as the presence of outburst risk, it is obvious that among the 20 sets of data, 10 sets are predicted to have outburst risk, in consistence with the facts. Although the prediction indexes of the 5-th and 8-th sets were lower than their critical values, both gas spurt and drill suction dynamic phenomena occurred. In other words, the dynamic phenomenon with low index outburst appeared. However, the BDA model accurately predicated these two low index outburst risks. Thus, the BDA prediction model can accurately forecast coal and gas outburst risk. Meanwhile, it is clear from Table 2 that the BDA model can also exactly predict no outburst risk cases. Thus, the BDA prediction model shows no misprediction.

From above, our BDA model for coal and gas outburst prediction can accurately predict outburst risk with accuracy rate of 100%. Thus it is a good method for coal and gas outburst prediction. The model utilizes a comprehensive relationship between different indexes and outburst risk to forecast coal and gas outburst and doesn't need to determine the critical values of predictors. The method is highly accurate, fast, and simple, and has broad application prospect in coal and gas outburst prediction.

6. Conclusions

Coal and gas outburst are greatly threatening the safety of underground workers and mining production, thus accurately predicting coal and gas outburst is crucial. With the mining depth extending, coal and gas outburst become increasingly complex, making the use of single index critical value prediction method for outburst risk more and more difficult. In order to cope with the challenge, in this paper,

- We analyzed the indexes for coal and gas outburst prediction and the factors affecting coal and gas outburst, and constructed the Bayes discriminant prediction index system consisting of the drill cuttings weight S, the drill cuttings gas desorption index Δh_2, gas content W, the gas initial diffusion velocity index ΔP, the EMR intensity E and number of pulse N.
- We introduced the Bayes discriminant analysis (BDA) as the prediction method, established the BDA model for coal and gas outburst prediction, and applied the model. The results indicated that the model has zero misjudgment and is very stable and accurate.
- We further applied the model in 20 sets of on-site data from Liangbei Coal Mine working face. The results showed that the BDA prediction model has 100% accuracy and zero mis/missed prediction and is able to accurately predicate outburst with low index dynamic phenomenon.
- Overall, the BDA model established in the paper can

accurately forecast coal and gas outburst and the method can be applied to other coal mine with geological conditions similar to Liangbei Coal Mine.

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