ГИАБ. Горный информационно-аналитический бюллетень /
MIAB. Mining Informational and Analytical Bulletin, 2022;(10-1):116–127
ОРИГИНАЛЬНАЯ СТАТЬЯ / ORIGINAL PAPER

УДК 622 DOI: 10.25018/0236_1493_2022_101_0_116

ОЦЕНКА РИСКА АВАРИЙ С ВЫБРОСАМИ УГЛЯ И ГАЗА НА УГОЛЬНЫХ ШАХТАХ НА ОСНОВЕ ФАКТОРНОГО АНАЛИЗА И ЛОГИСТИЧЕСКОЙ РЕГРЕССИИ

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Аннотация: Выбросы угля и газа представляют опасность для жизни шахтеров и безопасного производства в угольных шахтах. Для количественной оценки воздействия сопутствующих факторов на выбросы угля и газа и определения рисков выбросов были приняты 20 индексов причин аварий, которые составляют систему показателей причин аварий. Изучена взаимосвязь между риском выброса и окружающей средой, управлением и другими факторами с помощью факторного анализа (ФА). Разработана модель логистической регрессии (ЛР) для оценки безопасности угольных шахт. В соответствии с характеристиками распределения выборки, полученными методом начальной загрузки, классы безопасности угольных шахт были разделены на четыре уровня. Точность оценки модели ЛР для угольных шахт с выбросами и без них составила 94 и 85% соответственно. Фактор управления определяется как наиболее вероятный причинный фактор. Результаты показывают, что метод ФА и ЛР осуществим и применим для анализа и предотвращения аварий с выбросами угля и газа.

Ключевые слова: выбросы угля и газа, факторный анализ, логистическая регрессия, метод размножения выборок, оценка риска.

Благодарности: Авторы выражают признательность за помощь Китайскому горно-технологическому университету. Работа выполнена при поддержке Национального проекта ключевых исследований и разработок Китая [Номер гранта: 2017YFC0804408].

Для цитирования: *Ли Сяньгун, Ли Юй, Фа Цывэй, Алам Асар* Оценка риска аварий с выбросами угля и газа на угольных шахтах на основе факторного анализа и логистической регрессии // Горный информационно-аналитический бюллетень. — 2022. — № 10-1. — С. 116–127. DOI: 10.25018/0236_1493_2022_101_0_116.

Risk Assessment of Coal and Gas Outburst Accidents in Coal Mines Based on Factor Analysis and Logistic Regression

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Abstract: As one of the fatal hazards in coal mines, coal and gas outburst has been threatening the lives of miners and the safe production of coal mines. To quantify the impacts of associated factors on coal and gas outburst and determine the outburst risks, 20 accident causation

indexes were adopted to constitute the accident causation indicator system. Then, this study investigated relationship between outburst risk and environment, management and other factors through Factor Analysis (FA). Besides, Logistic Regression (LR) model was developed to percept the safety situation of coal mines. Finally, according to the characteristics of sample distribution obtained by the Bootstrap method, the safety grades of coal mines were divided into four levels and relevant suggestions were offered. The assessment accuracy of the LR model for the coal mines with outburst accidents or not were 94%, and 85% respectively. The management factor is determined as the most likely caused factor. The results reveal that the method of FA and LR is feasible and applicable in analysing and avoiding the occurrence of coal and gas outburst accidents.

Key words: Coal and gas outburst; Factor Analysis; Logistic Regression; Bootstrap; Risk assessment.

Acknowledgments: The authors would like to acknowledge the assistance the China University of Mining and Technology. This work is supported by the National Key Research and Development Project of China [Grant numbers: 2017YFC0804408].

For citation: Li Xiangong, Li Yu, Fa Ziwei, Alam Easar Risk Assessment of Coal and Gas Outburst Accidents in Coal Mines Based on Factor Analysis and Logistic Regression. *MIAB. Mining Inf. Anal. Bull.* 2022;(10-1):116–127. [In Russ]. DOI: 10.25018/0236_1493_2022_101_0_116.

1. Introduction

Coal plays a major role in meeting the energy demands in China, the safe production of which contributes to Chinese economic development [1]. With the increasing mining depth, the mining environment tends to be increasingly complex, which has a lot to do with the occurrence of gas accidents. Three major gas accidents are gas explosion, gas asphyxiation and coal and gas outburst. The cumulative proportion of coal and gas outburst accidents accounts for 42.3% of the total number of gas accidents. The more complex occurring mechanisms of outburst compared with the other two accidents [2] makes it difficult to assess its risk accurately. So, it is urgent to evaluate the outburst risk to avoid potential losses.

The risk assessment of outburst has attracted many scholars' attention. Zhou proposed a quantitative method according to the gas dynamic characteristics of coal and gas outburst [3]. Kursunoglu adopts a structural equation model to analyse the multiple interactions between the parameters affecting coal and gas outbursts [4]. Rudakov developed a mathematical model of gas flow to calculate gas pressure changes in the pores initiated by gas release [5]. Xue adopted energy approach to explain the outburst process and concluded that the outburst risk could be minimized by reducing coal seam gas energy [6]. Black analysed the main factors causing outburst accidents in terms of abnormal geological conditions and gas content [7]. Liu studied the changes of the roof and floor displacement and coal seam permeability, proving the feasibility of using ultrathin protective seam drilling combined with stress-relief gas drainage to eliminate the dangers of coal and gas outburst [8]. Wei revealed the mechanism of extreme gas emission after disturbance induced by rockburst by developing a gas-solid simulation software based on a stress equation and permeability model [9].

The occurrence of coal and gas outburst accidents is a comprehensive result of geological environment [10], technical measures and improper management [11].

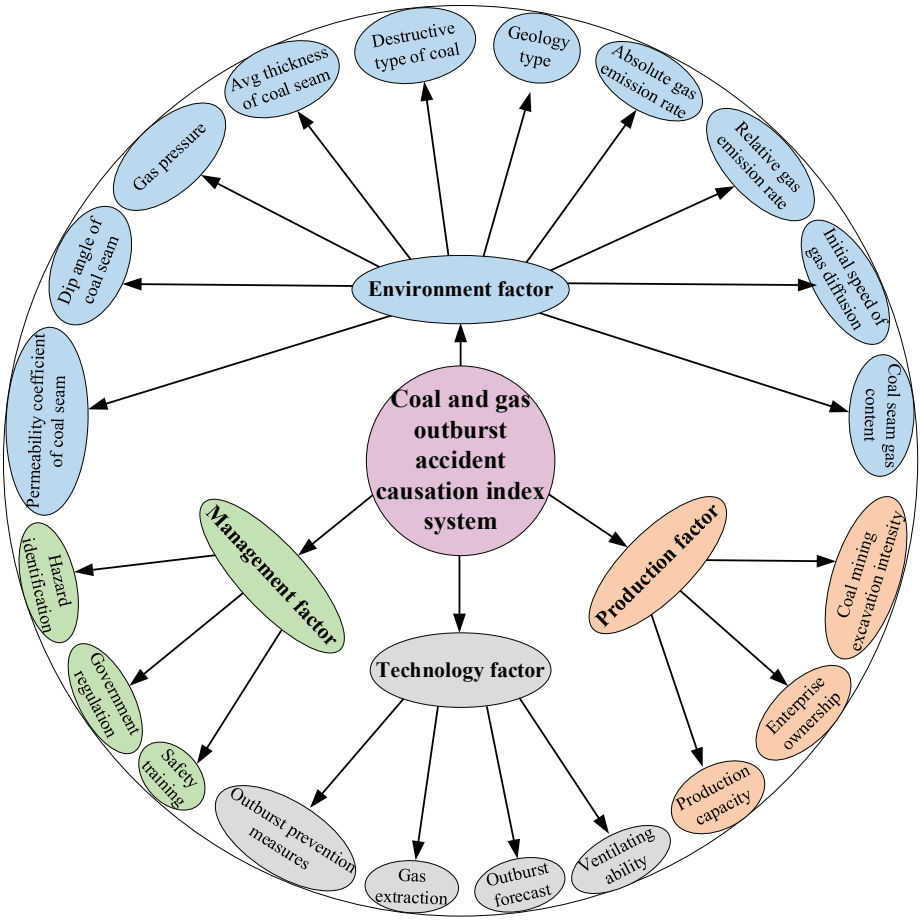

Fig. 1. Coal and gas outburst accidents causation index system

This study involves risk assessment by summarizing the risk factors regarding different sources[12]. Then FA and LR are combined to assess the outburst risk. Besides, due to the insufficient data samples of outburst accidents, the Bootstrap method is adopted for sample expansion. The guidance for production operation is finally provided for different risk levels.

2. Coal and gas outburst accident causation index system

Among the direct causes of coal mine accidents in China, the human factor [13] accounts for more than 90% [14]. Therefore, this paper constructed the accident causation system, considering the environment factor, the production factor, the technology factor and the management factor [15], as shown in Fig. 1.

The system involves 20 indexes, which analyse the occurrence of coal and gas outburst accidents comprehensively. The indicators are named from X_1 to X_{20} in order from *Permeability coefficient of the coal seam* to *Hazard identification* and are divided into four factors. Among them, the environment factor reflects the natural conditions that have a great influence on the occurrence of outburst accidents. The production factor reflects the production

information of coal mines. The technology factor refers to the technical efforts made by coal mines to avoid accidents. The management factor reflects the safety management risk that may causes outburst accidents.

3. Methods

Due to the information overlap caused by high dimensionality of accidents data, FA is adopted to realize data compression [16]. Then, the compressed indexes are used as the independent variables of the LR model, so as to assess the risk of coal and gas outburst accidents. Compared with general statistical events, outburst accidents have a high occurrence cost and a small number of samples, making it difficult to meet the requirements of classical statistical methods for sample size. Thus, the Bootstrap method is adopted to expand the data samples. The risk levels of the accidents are divided according to the distribution characteristics of the data, with corresponding protective measures proposed.

3.1. Factor Analysis

The adoption of FA is to transform relevant observable variables into independent and latent variables, namely common factors, which can reflect the main information of the original data while reducing the number of the variables [17]. The transformation steps are as follows:

(1) Data standardization

Data standardization is conducted before data dimensionality reduction. If the number of original observation variables is p, and the sample observation data matrix X is formed, then

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}. \quad (1)$$

With Eq. (2) to standardize Eq. (1),

$$x'_{ij} = \frac{x_{ij} - \overline{x}_j}{\sqrt{Var(x_j)}},$$
$$i = 1,2,\ldots,n; j = 1,2,\ldots,n, \quad (2)$$

Where $\overline{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$

and

$$Var\left(x_j\right) = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \overline{x}_j)^2 (j = 1,2,\ldots,p).$$

(2) Covariance matrix

After data standardization X' is obtained, whose covariance is C, then

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1p} \\ c_{21} & c_{22} & \cdots & c_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{np} \end{bmatrix}, \quad (3)$$

where

$$c_{ij} = \mathrm{cov}\left(x_i, x_j\right) = \frac{\sum_{k=1}^{n}(x_i - \overline{x}_i)(x_j - \overline{x}_j)}{n-1}, n > 1.$$

(3) Eigenvalues and eigenvectors and number of common factors

For Eigenvalues λ_i, eigenvectors

$\alpha_i = (\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{ip})$, $i = 1, 2, \ldots, p$.

The accumulated value of common factor can be denoted as f_i, defined by

$$f_i = \frac{\lambda_i}{\sum_{i=1}^{p}\lambda_i}. \quad (4)$$

The number of common factors, k is determined by the principle that the cumulative contribution rate should be more than 80%.

(4) Factor loading matrix

Then p variables can be written as a linear combination of n factors from F_1 to F_n, in matrix terms, there is

$$X = AF + \varepsilon X = AF + \varepsilon, \quad (5)$$

Where F_i (i = 1, 2, ..., n) are common factors, whose coefficients are the factor loadings, A. Here, ε represents latent stochastic error terms with zero mean and finite variance [18].

3.2. Logistic Regression

As one of the common methods of data mining and machine learning, LR analyses and predicts discrete dependent variables based on one or more continuous or discrete independent variables [19]. The LR model can be expressed as

$$\mathrm{Prob}(\mathrm{event}) = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\ldots+b_px_p)}}, \quad (6)$$

where b_0, b_1, ... , b_p are the LR coefficients.

A nonlinear LR model can be established on the basis of available data to assess the occurrence rate of the event. The value range of *Prob(event)* is within [0,1]. That is, the closer the final output is to 1, the higher the probability of the event occurring.

3.3. Bootstrap method

The Bootstrap method is proposed by Efron in 1979 [20]. Since the samples are from the total, the subsamples obtained by resampling can also reflect the characteristics of the total. The sampling process is shown in Fig. 2.

The test data is denoted as $Y = \{(a_i, b_i), i=1,2, \cdots, N\}$, from which a subsample, $A_j = \{A_{1,j}, A_{2,j}, .., A_{N,j}\}$, of the same sample size as the original test data, can be obtained by randomly sampling N times with put-back. Then the statistical estimation is conducted based on the sub-samples to obtain the sampling distribution [21].

4. Case study

By summarizing the outburst accident reports in China, 30 sets of data are obtained according to the outburst accident causation system. To eliminate the repeatability among indexes, the FA method is performed to reduce the dimension of the indexes. Then LR is carried out to assess the risk of coal and gas outburst accidents.

4.1. Factor Analysis

(1) KMO test and Bartlett test

The KMO test and Bartlett test are conducted to verify whether the data is qualified [22]. For this study, the KMO sampling moderate measurement value is 0.802. The approximate chi-

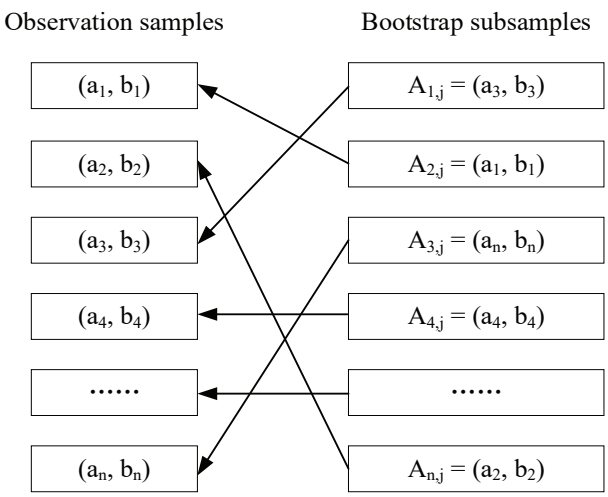

Fig. 2. Sampling process of Bootstrap

Table 2
Eigenvalues and variance contribution rates

Eigenvalue	The value of eigenvalue	Variance contribution rates	Cumulative variance contribution rates
λ_1	5.9944	29.972%	29.972%
λ_2	3.4209	17.104%	47.077%
λ_3	2.8276	14.138%	61.215%
λ_4	1.9074	9.537%	70.752%
λ_5	1.5078	7.539%	78.291%
λ_6	1.0301	5.150%	83.441%

Table 3
Factor loading matrix after rotation

	F_1	F_2	F_3	F_4	F_5	F_6
Government regulation	0.935	−0.017	0.225	0.004	0.170	−0.007
Outburst prevention measures	0.916	0.029	0.174	0.113	−0.033	−0.258
Safety training	0.851	−0.202	−0.052	−0.103	0.227	0.163
Outburst forecast	0.849	0.014	0.040	−0.009	0.195	0.088
Hazard identification	0.788	−0.287	0.1649	0.166	−0.397	−0.028
Initial speed of gas diffusion	−0.306	0.900	−0.041	−0.135	−0.068	0.080
Permeability coefficient of coal seam	−0.313	0.839	0.025	−0.171	−0.204	−0.163
Relative gas emission rate	0.369	0.769	−0.043	0.205	0.065	0.026
Avg thickness of coal seam	0.201	−0.208	0.862	0.153	0.133	−0.194
Destructirve type of coal	−0.170	0.346	0.775	0.006	−0.145	−0.254
Geology type	0.354	−0.254	0.701	0.131	−0.313	−0.041
Coal seam gas content	0.380	0.461	0.520	0.412	0.044	0.153
Production capacity	−0.294	−0.079	0.060	0.856	0.131	0.067
Enterprise ownership	0.447	0.096	0.165	0.770	−0.268	−0.142
Ventilating ability	0.183	−0.388	0.336	0.565	−0.088	−0.458
Coal mining excavation intensity	0.266	−0.069	−0.082	−0.193	0.846	0.182
Gas pressure	0.003	−0.106	−0.039	0.128	0.686	−0.221
Absolute gas emission rate	0.284	0.126	0.400	0.120	0.203	−0.671
Gas extraction	0.402	0.343	0.283	−0.034	0.409	−0.433
Dip angle of coal seam	0.203	0.054	−0.065	0.015	0.027	0.835

square significance probability is 0.000, indicating its qualification for FA.

(2) Eigenvalues and variance contribution rates

The eigenvalues and variance contribution rates are ranked in order of eigenvalues up to a cumulative variance contribution of 80%, as shown in Table 2.

In Table 2, the cumulative variance contribution rate of the first six characteristic values reaches 83.441%, indicating that the 6 common factors contain 83.441% of the original information. Therefore, these six factors are adopted for the subsequent analysis.

(3) FA after rotation

Then, the rotating factor loading matrix is obtained as shown in Table 3.

According to the factor loading matrix after rotation, the causation system of

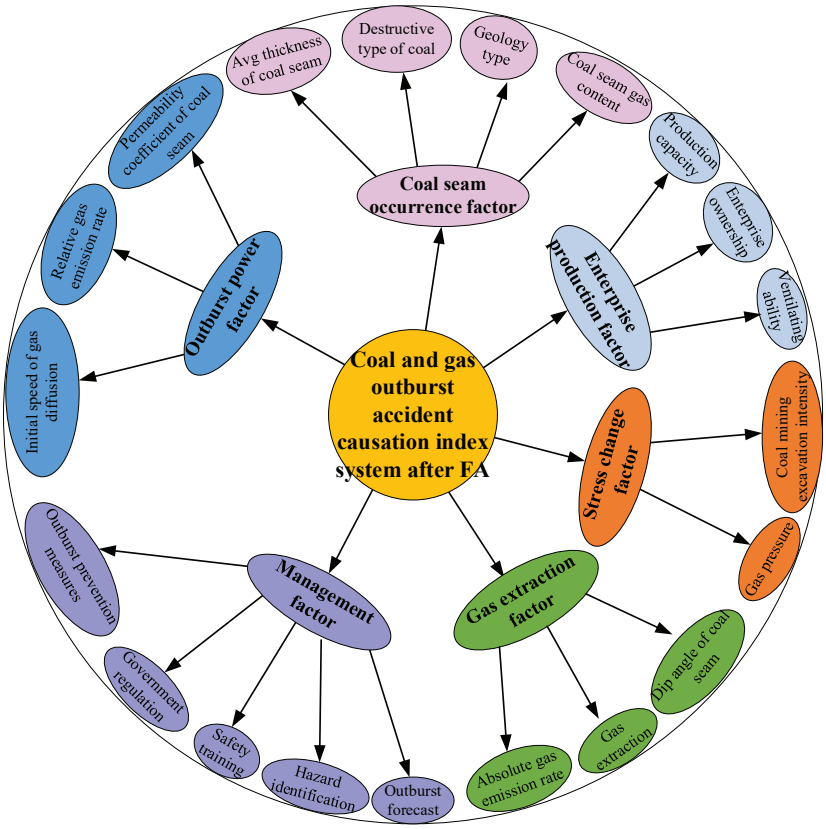

Fig. 3. Coal and gas outburst accident index system after FA.

outburst accidents can be reclassified as shown in Fig. 3.

The accident causation system formed after FA is different from that based on subjective experience in Fig. 1. The index system after FA is divided into six factors. Classification of accident causation system from the perspective of the relevance of each factor ensures the high relevance in one factor and low correlation between factors, effectively avoiding the impact of subjective arbitrariness, and explaining the composition of the system reasonably. Factor F_1 is affected by confusion in safety management, inadequate safety training and government regulation, named as the management factor. Factor F_2 is named as the outburst power factor, considering that it is influenced by the initial speed of gas diffusion, relative gas emission rate and permeability coefficient of the coal seam. Factor F_3 is influenced by average thickness, geology type of coal seam, destructive type of coal and coal seam gas content, named as the coal seam occurrence factor. Factor F_4 is named as the enterprise production factor because it is influenced by production capacity, enterprise ownership, and ventilating ability. Factor F_5 is mainly affected by coal mining excavating intensity and gas pressure. So, it is named the stress change factor. Factor F_6 is mainly affected by absolute gas emission rate, gas extraction and dip angle of the coal seam, accounting for the reason why F_6 is named as the gas extraction factor.

4.2. Coal and gas outburst risk assessment

According to the linear relationship obtained by FA, 30 sets of accident data are substituted to obtain the corresponding 30 groups of common factors. The accident results of data are denoted as Z. When $Z = 1$, the accident occurs; when $Z = 0$, the accident does not occur. Among the 30 sets of data, the Z-value of 13 groups of data is 1 and the remaining 17 groups' ones are 0. Therefore, the cut-off value is 0.57, and the relation between the accident probability *Prob(event)* and the accident result Z is

$$Z = \begin{cases} 0, & 0 \le \mathrm{Prob}(\mathrm{event}) \le 0.57 \\ 1, & 0.57 < \mathrm{Prob}(\mathrm{event}) \le 1 \end{cases} \quad (7)$$

For regression analysis, the z-value of accident results is supposed to be transformed into the occurrence probability of coal and gas outburst accident, *Prob(event)*. Take the average of *Prob(event)* in the interval. Consequently, when $Z = 1$,

$\mathrm{Prob}(\mathrm{event}) = \frac{0.57+1}{2} = 0.785$. When

$Z = 0$, $\mathrm{Prob}(\mathrm{event}) = \frac{0+0.57}{2} = 0.285$.

The occurrence probability of accidents and the common factor F_i are substituted into the LR model. The LR model is obtained as shown in Eq. (8).

$$\mathrm{Prob}(\mathrm{event}) = \frac{1}{1+e^{-(1.91-0.31F_1+0.06F_2+0.25F_3-0.18F_4-0.06F_5+0.22F_6)}} \quad (8)$$

R^2 represents the degree of fit, which is also called the determination coefficient or goodness of fit. The value range of R^2 is within [0,1]. The closer R^2 is to 1, the better the fitting degree of the regression model will be. The R^2 of the LR model is 0.3797, indicating its poor interpretability. The assessment results of the model are shown in Table 4.

Suppose that the data samples of accident occurrence are positive samples, and vice versa are negative ones. In Table 4, for the negative samples, the logistic regression achieves the accuracy of [23] 88% while that of positive samples is 69%. The model's fitting degree and discriminant accuracy are poor, the derived variables of each common factor F_i are thus introduced to improve the fitting.

4.3. Optimization of the model

A derived variable is introduced to each factor, that is, a mathematical function adopted to act on each factor respectively. Meanwhile, the relationships between variables will also change. Therefore, the R^2 of the model can be optimized. Partial transformation results of common factors are shown in Table 5.

The derived variables change the value of R^2. But not all transformations are beneficial. The transformation of F_2 contributes the most to the improvement. $1/F_2$ is thus introduced into the model. The value of R^2 is improved from 0.3797 to 0.7473. The confusion matrix after the introduction of derived variables is shown in Table 6.

The assessment accuracy of the transformed LR model is 94% for the negative sample and 85% for the positive samples, indicating that the fitting degree of the LR model is significantly improved. The LR model is shown in Eq. (9).

$$\mathrm{Prob}(\mathrm{event}) = \frac{1}{1+e^{-(1.91-0.31F_1+0.06F_2^{'}+0.25F_3-0.18F_4-0.06F_5+0.22F_6)}}. \quad (9)$$

4.4. Discussion

According to Eq. (8), the probability of coal and gas outburst accidents in 30 coal mines can be obtained. The frequency statistics of the accidents are shown in Fig. 4.

In Fig. 4, the accident probability is concentrated in the interval (0, 0.1] and (0.9, 1]. Nevertheless, due to the small sample size, the distribution characteristics may vary from those of the actual values [24]. Besides, the distribution boundaries of the probability interval are not significant. 30 sample data are hence used as the original samples of the Bootstrap method, and the sample is randomly and repeatedly sampled with some replacement [25]. The booting results can be seen from Fig. 5 to Fig. 8.

The sample size is set as N_1 = 1000, N_2 = 5000, N_3 = 10000 and N_4 = 20000. When the sample size is more than 10000, the data distribution characteristics will not change significantly. Thus, the distribution of the assessment interval of the accident situation is divided according to Fig. 7. In Fig. 7, the probability of coal and gas outburst accidents in most coal mines

Table 4
Confusion matrix

Classification	Assessed probabilities	
True probabilities	0.285	0.785
0.285	15	2
0.785	4	9

Table 5
Comparison of the effect of partial common factor transformation.

Factor	Transmission type	R^2
F_1	exponential	0.1966
F_2	reciprocal	0.7473
F_3	logarithm	0.3371
F_6	square	0.5081

Table 6
Confusion matrix after introducing a derived variable.

Classification	Assessed probabilities	
True probabilities	0.285	0.785
0.285	16	1
0.785	2	11

Table 7
The risk level of coal and gas outburst accidents.

Risk level	I	II	III	IV
Interval	[0,0.26]	(0.26,0.47]	(0.47,0.80]	(0.80,1]

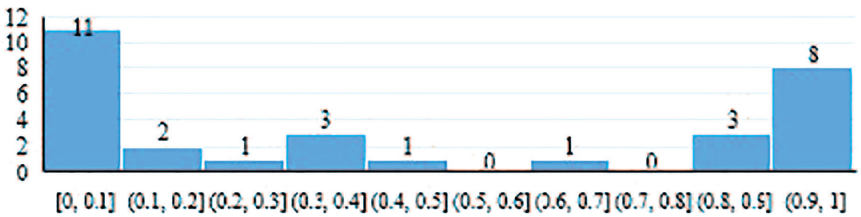

Fig. 4. Frequency statistics of 30 accidents

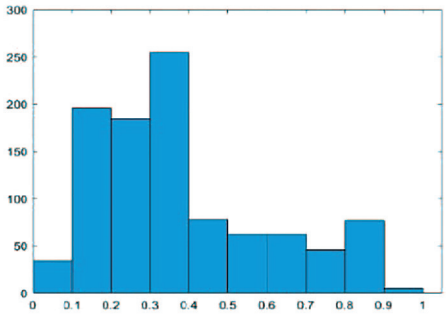

Fig. 5. 1000 sampling results

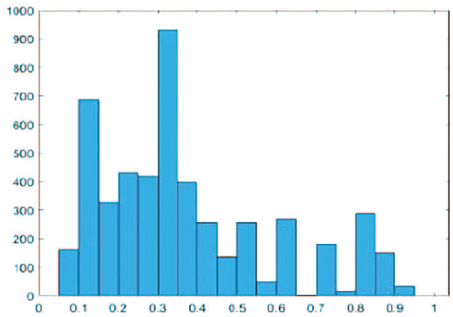

Fig. 6. 5000 sampling results

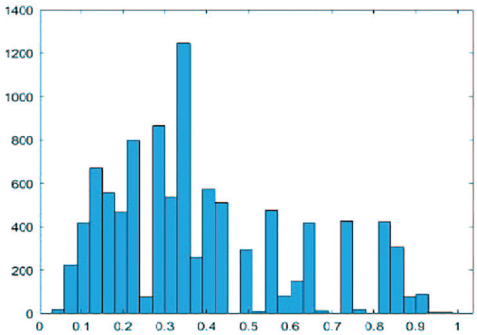

Fig. 7. 10000 sampling results

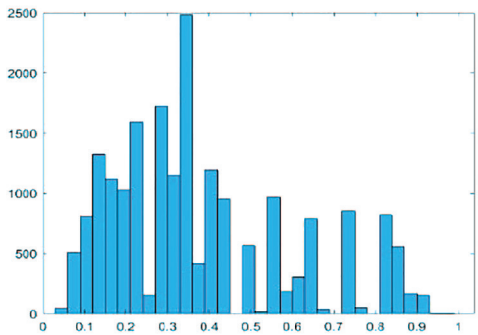

Fig. 8. 20000 sampling results

is below 0.57, that is, the probability of outburst accidents in most coal mines is small, which is consistent with traditional experience. The risk level of coal and gas outburst accidents is divided into four levels accordingly. Each level corresponds to the accident probability interval is shown in Table 7.

With accident probability interval within [0, 0.26], there is little possibility of an outburst accident. Daily outburst prevention and maintenance should be given priority to in coal mines. As the accident probability interval within (0.26, 0.57], attention is supposed to be paid to the anomalies during underground operations to prevent the accident situation level from evolving to a worse level. When the accident probability interval is (0.57, 0.80], importance needs to be attached to the improvement of the outburst hazards awareness and timely elimination of the forebodings of outburst accidents during the excavating and mining operations. When the accident probability interval is (0.80, 1], the possibility of outburst accidents is high. In this context, the operation of the working face of the warning should be suspended. Also, itemization of hidden dangers should be conducted and risk symptoms should be eliminated according to safety management guidance.

5. Conclusion

Aiming to provide support to the safety management of coal mine production, this paper applies Factor Analysis and Logistic Regression for risk assessment analysis of coal and gas outburst accidents. Through the Factor Analysis, 20 indexes are aggregated into 6 factors, among which the management factor could account

for 30.0% information of the accident causation. The accuracy rate of the Logistic Regression model to assess the outburst probability is up to 94%. By dividing the risk level into four grades, corresponding measures are proposed in advance for risk reduction.

The FA-LR model also has some limitations. Indexes such as government regulations and safety training are Boolean variables, contributing little to data richness. Besides, the data in this study is static. Our subsequent research will focus on the dynamic data collected from different coal mines and adopts the Bayesian Network method to develop a real-time assessment system for coal and gas outburst safety management.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that influence the work reported in this paper.

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Получена редакцией 20.03.2022; получена после рецензии 27.06.2022; принята к печати 10.09.2022.
Received by the editors 20.03.2022; received after the review 27.06.2022; accepted for printing 10.09.2022.