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Cloud model based on a novel analytic hierarchy process for rockburst liability prediction

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Abstract

Rockburst is a common geological hazard in underground mining and excavating, constituting a serious threat to the safety of workers and equipment. Rockburst liability prediction is of crucial significance to the prevention of rockburst hazards. Multi-criteria decision-making approach is an effective tool to predict rockbursts. In this paper, five empirical factors (strength-stress ratio, Russenes criterion, brittleness index, strain energy storage index, and integrity index) were used to construct the standard of rockburst liability. A novel analytic hierarchy process (AHP) was proposed to determine the weight of these factors, and then a cloud model was established for rockburst liability prediction on this basis. In the new AHP, the random errors induced by the pairwise comparison matrices of decision-makers were corrected according to the Bayesian theories. Nine cases from engineering projects in China were collected to validate the proposed model for rockburst liability prediction, and the prediction results were consistent with the field status. The quantitative index (Euclidean distance) indicates that the novel analytic hierarchy process has better performance than the original analytic hierarchy process in the weight calculation of factors; the new proposed cloud model is also superior to the original cloud model and the technique for order preference by similarity to an ideal solution model in the prediction of rockburst liability.

Keywords: rockburst liability prediction; multi-criteria; analytic hierarchy process; cloud model

1 Introduction

Rockburst is an important research topic in rock mechanics and engineering geology (Li et al., 2007; Hegde and Rokseth 2020; Zhang et al., 2021), which is generally considered as a dynamic instability phenomenon. Rockburst prediction in initial stages of design has a remarkable role on enhancement of safety (Ghasemi et al., 2020). However, due to the suddenness and uncertainty of rockbursts, the complex mechanisms of rockburst are still not fully understood (He et al., 2015). Fig. 1 shows some typical accidents induced by rockbursts. As can be seen from Fig. 1, rockbursts may cause damages to roadways, shearers, and ground buildings.

The formation mechanism and classification of rockbursts have been tackled by many researchers with various methods, and many valuable conclusions have been achieved (e.g., He et al., 2012; Su et al., 2018). Meanwhile, how to predict rockburst scientifically and accurately has always attracted people's attention. In order to determine whether rockburst occurs, a set of determination indicators of rockburst have been proposed (e.g., Russebes 1974; Kidybinski 1981; Wang et al., 1998; Wang and Park 2001). Some assessment indexes for rockburst liability prediction are listed in Table 1. Among these indexes, the most practical indexes for engineering applications are Russenes criterion (Russebes 1974), brittleness index (Wang et al., 1998) and strain energy storage index (Kidybinski 1981). In Table 1, the Russenes criterion is the ratio of tangential stress around underground excavations to uniaxial compressive strength, and the brittleness index is the ratio of uniaxial compressive strength to tensile strength. The strain energy storage index is the ratio of elastic strain energy to dissipated strain energy in the stress-strain curve. Although single index evaluation is an easy

and applicable alternative, which has been proved to be useful in many engineering projects, it ignores the effect of geo-mechanical and technological conditions. This causes unilateral, one-sided and limited results (Wang et al., 2008; Zhou et al., 2012, 2016).

In order to improve the prediction accuracy of rockburst liability, multi-criteria approaches have been gradually developed (e.g., Wang et al., 1998; Wang et al., 2015; Li et al., 2018; Pu et al., 2019; Xue et al., 2020a; Mahmoodzadeh et al., 2021; Yin et al., 2021; Zhou et al., 2021). As the name implies, the multi-criteria approaches select multiple indexes to predict rockburst liability. Up to now, a set of prediction methods have been proposed based on the application of multi-criteria approaches for rockburst liability prediction (Table 2). Several mathematical models involving intelligent techniques have been proposed for rockburst liability prediction such as support vector machine model (Pu et al., 2019), extreme learning machine (Xue et al., 2020b), grey model (Zhou et al., 2019), extension model (Xue et al., 2019), and fuzzy model (Pu et al., 2018). The approaches listed in Table 2 can be further divided into two types: multi-criteria decision-making approach (Liao et al., 2014) and multi-criteria machine learning approach (Li et al., 2020). The classification criteria of rockburst liability should be established in advance in the multi-criteria decision-making method (Afraei et al., 2019). In the machine learning method, rockburst liability prediction is regarded as a two-class or multi-class problem. Pu et al. (2019) noted that the accuracy of machine learning approaches depends heavily on the size of rockburst case databases used. However, the size of rockburst case databases is typically around 200, which may lead to inaccurate predictions.

The analytic hierarchy process (AHP) is an effective approach for weight calculation in

multi-criteria decision-making problems (Saaty 1980). The core of AHP is to construct pairwise comparison matrices (PCM). When the original AHP is applied in the prediction of rockburst liability, the random error induced by the PCM of decision-makers is inevitable, but the impact of random error is not considered. With the help of Bayesian theory, the impact of random error on weight can be corrected (Press 1989). The combination of AHP and cloud model (a mathematical method considers both the randomness and fuzziness of variables for solving multi-criteria evaluation problems) (Li et al. 2009; Wang et al., 2014) can effectively predict rockburst liability.

In summary, the main objective of this paper was to propose a new model (a cloud model based on the novel analytic hierarchy process) for rockburst liability prediction. In Section 2, a novel AHP based on the Bayesian theory was described in detail. In Section 3, a cloud model based on the novel AHP was introduced. In Section 4, nine cases from engineering projects in China were evaluated to validate the proposed model. Section 5 is discussion. Conclusions were drawn in the end.

2 A novel analytic hierarchy process

2.1 Original analytic hierarchy process

Analytic hierarchy process (AHP) is an accurate approach for quantifying the weights of decision criteria. A PCM can be structured according to one to nine scales in the AHP (Saaty 1980). Let's take $A = (a_{ij})_{n \times n}$ as the PCM, where a_{ij} is the relative importance of factor i compared with factor j , and

$$\begin{cases} a_{ij} = 1/a_{ji}, & (i \neq j) \\ a_{ij} = 1, & (i = j) \end{cases}, i, j = 1, 2, \dots, n \quad (1)$$

In the PCM, the weight $W = (w_i)_{n \times 1}$ of factors can be determined by the eigenvector

100 method, namely:

$$101 \quad \begin{aligned} &AW = \lambda_{\max} W, \\ &\text{subject to } \sum_{i=1}^n w_i = 1, w_i \geq 0 \end{aligned} \quad (2)$$

102 where, $\lambda_{\max}$ is the maximum principal eigenvalue of the PCM. In addition to the eigenvector
103 method, other commonly used methods for weights calculation include the geometric mean
104 method and the least squares method. However, the geometric mean method lacks a sufficient
105 theoretical basis, and the calculation of the least squares method is very complicated. A
106 consistency ratio (CR) was used to measure the consistency level of the PCM, denoted by

$$107 \quad CR = \frac{\lambda_{\max} - n}{RI(n-1)} \quad (3)$$

108 where, RI is the random consistency index. A PCM with $CR < 0.1$ is acceptable ($CR = 0.1$
109 means that the judgments by decision-makers are 10% as inconsistent). Otherwise, one should
110 revise it until $CR < 0.1$.

111 2.2 Revising analytic hierarchy process

112 Although the original AHP is simple, it does not fully consider the impact of
113 decision-maker's bias on results. Given this, the PCM obtained always has an error, namely:

$$114 \quad a_{ij} = \frac{w_i}{w_j} e_{ij} \quad (4)$$

115 where e_{ij} is the error term following the lognormal distribution (Escobar and
116 Moreno-Jiménez 2000), and

$$117 \quad \begin{cases} e_{ij} = 1/e_{ji}, & (i \neq j) \\ e_{ij} = 1, & (i = j) \end{cases}, i, j = 1, 2, \dots, n \quad (5)$$

118 Since a_{ij} follows the lognormal distribution, $\ln(a_{ij})$ follows the normal distribution.

119 Without loss of generality, let $\ln(a_{ij}) : N(u_{ij}, \sigma^2)$, where u_{ij} (an unknown parameter) is the
120 expectation of $\ln(a_{ij})$ and σ^2 (to be known) is the variance of $\ln(a_{ij})$. The prior

distribution $\pi(u_{ij})$ of u_{ij} follows the normal distribution $N(\theta_{ij}, \tau^2)$ (both θ_{ij} and τ^2 are known). The posterior distribution $\pi(u_{ij}|a_{ij})$ of u_{ij} also follows the normal distribution $N(b_{ij}, \tau'^2)$, where (Press 1989)

$$b_{ij} = \frac{\sigma^2 \ln(a_{ij}) + \tau^2 \theta_{ij}}{\sigma^2 + \tau^2} \quad (6)$$

$$\tau'^2 = \frac{\tau^2 \sigma^2}{\tau^2 + \sigma^2} \quad (7)$$

where, $\sigma^2 = 0.5$ according to the Bayesian statistics theory (Bernardo and Smith 1994).

One can use the following equations to obtain θ_{ij} and τ^2 of the prior distribution $\pi(u_{ij})$ of u_{ij} (Press 1989):

$$\theta_{ij} = \ln(\mathbb{W}_i) - \ln(\mathbb{W}_j) \quad (8)$$

$$\mathbb{W}_i = \left(\prod_{j=1}^n a_{ij} \right)^{1/n} \quad (9)$$

$$\tau^2 = \frac{1}{n(n-1)} \sum_{i \neq j}^n \left[\ln(a_{ij}) - \ln(\mathbb{W}_i / \mathbb{W}_j) \right]^2 \quad (10)$$

According to the relationship between lognormal distribution and normal distribution, the Bayesian revision matrix (BRM) can be denoted by

$$B = \left(\exp(b_{ij}) \right), i, j = 1, 2, \dots, n \quad (11)$$

According to the BRM, the weight $W = (w_i)_{n \times 1}$ of factors can be obtained by the eigenvector method, namely:

$$BW = \lambda_{\max} W, \text{ subject to } \sum_{i=1}^n w_i = 1, w_i \geq 0 \quad (12)$$

where, $\lambda_{\max}$ is the maximum principal eigenvalue of the BRM. Consistency ratio (CR) is used to measure the consistency level of the BRM. In the new AHP, the PCM in standard AHP is replaced by the BRM.

The implementation steps of the new AHP are as follows:

Step 1: Input a PCM $A = (a_{ij})_{n \times n}$ according to one to nine scales.

Step 2: Calculate θ_{ij} and τ^2 in the prior distribution $\pi(u_{ij})$ of u_{ij} by using Eqs. (8)-(10).

Step 3: Calculate b_{ij} in the posterior distribution $\pi(u_{ij}|a_{ij})$ of u_{ij} by using Eqs. (6)-(7).

Step 4: Establish a BRM by using Eq. (11).

Step 5: Calculate the weight $W = (w_i)_{n \times 1}$ of factors by using Eq. (12).

3 Approach for rockburst liability prediction

3.1 Cloud model

A cloud model is a mathematical method for solving multi-criteria evaluation problems considering both the randomness and the fuzziness of variables (Li et al., 2009; Wang et al., 2014). A cloud represents a concept (or object) with a ternary operator (E_x, E_n, H_e) (Fig. 2), where E_x is the expectation; E_n is the entropy, an uncertainty measurement of qualitative concepts, which is determined by both the randomness and the fuzziness of the concepts; H_e is the excess entropy, which is a redescription of the uncertainty of entropy. The ordinate in Fig. 2 represents the degree of certainty (d).

A normal cloud generator can be implemented to obtain the certainty degree of a concept. The steps are as follows (Wang et al., 2014; Li et al., 2018):

Step 1: Input x (the concept), E_x , E_n , and H_e .

Step 2: Generate a normal random number $E'_n \sim N(E_n, H_e^2)$.

Step 3: Calculate the degree of certainty with the following formula:

$$d(x) = \exp\left(-\frac{(x - E_x)^2}{2E_n'^2}\right) \quad (13)$$

Step 4: Steps 2 and 3 are repeated N times, and the average value of the N certainty degrees is taken as the final certainty degree.

3.2 Cloud model based on novel analytic hierarchy process

It is necessary to establish a rockburst liability standard for rockburst liability prediction.

This paper directly referred to the classification criteria determined by Zhang et al. (2011) (Table 3), which consisted of five factors, i.e., strength-stress ratio, Russenes criterion, brittleness index, strain energy storage index, and integrity index. All five factors were dimensionless. The rockburst liability falls into four classes (I、II、III、IV), which are no rockburst, weak rockburst, moderate rockburst, and violent rockburst. The characteristics of class I are as follows: no stability problems caused by rock stresses and no noises generated. Class II: tendencies to crack and loosen of rock and light noises generated. Class III: considerable slabbing and loosening of rock, tendencies to develop a deformed periphery with time, and strong cracking noises generated. Class IV: severe rockfalls from roof and walls immediately after blasting, slabs pop from floor, considerable over-breaks and deforming of the periphery gun shot noises generated (Kidybinski 1981).

The ternary operator (E_x, E_n, H_e) in the cloud model can be obtained according to Table 3 by using following equations:

$$E_x = \frac{S_{\min} + S_{\max}}{2} \quad (\text{classes II and III}) \quad (14a)$$

$$E_x = S_{\min} \quad (\text{class I}) \quad (14b)$$

$$E_x = S_{\max} \quad (\text{class IV}) \quad (14c)$$

$$E_n = \frac{S_{\max} - S_{\min}}{6} \quad (15)$$

$$H_e = 0.01 \quad (16)$$

where, $S_{\max}$ and $S_{\min}$ represent the upper-bound and lower-bound of a level, respectively. By substituting E_x , E_n , and H_e into the normal cloud generator shown in Section 3.1, a deterministic matrix $D = (d_{ij})_{n \times 4}$ can be obtained, where d_{ij} represents the degree of certainty that factor i in object X belongs to class j . The membership vector $M = (m_i)_{1 \times 4}$ of object X belonging to each class can be obtained according to Eq. (17).

$$M = W' D \quad (17)$$

Determining the class of object X (i.e., predicted rockburst liability) as follows:

X is I, if $m_1 > m_2, m_3, m_4$

X is II, if $m_2 > m_1, m_3, m_4$

X is III, if $m_3 > m_2, m_1, m_4$

X is IV, if $m_4 > m_2, m_3, m_1$

The flow chart of the proposed approach for rockburst liability prediction was shown in Fig. 3. The proposed model was compiled in the form of MATLAB code according to Fig. 3.

4 Case analysis

4.1 Case description

Nine typical rockburst cases in China (Wang et al., 1998; Xu et al., 2018) were selected to validate the proposed new cloud model. The nine cases are Jingping I# tunnel, Jinping II# tunnel, Tianshengqiao II# hydropower station diversion tunnel, Taipingyi hydropower station diversion tunnel, Qinling railway tunnel, Dongguashan copper mine, Pubugou underground hydropower station underground tunnel, Yuzixi I# hydropower station diversion tunnel, and

Cangling tunnel (Table 4). For Case 1, the rockburst liability class is III according to the strength-stress ratio and strain energy storage index. According to the brittleness index and integrity index, the class of this case is I. According to the Russenes criterion, the class is IV. Due to inconsistent rockburst class for different factors, the proposed new cloud is an effective approach for solving multi-criteria evaluation problems, considering both the randomness and fuzziness of variables, which can be used to predict rockburst liability.

4.2 A demo of the proposed model

a) Calculate the weight of input factors

Here, we demonstrated the process for calculating the weights of strength-stress ratio, Russenes criterion, brittleness index, strain energy storage index, integrity index with the proposed AHP.

First, the PCM obtained according to one to nine scales is as follows:

$$A = \begin{bmatrix} 1 & 1/5 & 3 & 7 & 4 \\ 5 & 1 & 6 & 8 & 7 \\ 1/3 & 1/6 & 1 & 4 & 2 \\ 1/7 & 1/8 & 1/4 & 1 & 1/3 \\ 1/4 & 1/7 & 1/2 & 3 & 1 \end{bmatrix}$$

Second, the BRM is obtained according to Eqs. (4)-(11) as follows:

$$B = \begin{bmatrix} 1 & 0.26 & 2.61 & 6.79 & 3.66 \\ 3.87 & 1 & 5.69 & 10.42 & 7.33 \\ 0.38 & 0.18 & 1 & 3.65 & 1.81 \\ 0.15 & 0.10 & 0.27 & 1 & 0.38 \\ 0.27 & 0.14 & 0.55 & 2.60 & 1 \end{bmatrix}$$

Last, the obtained weights of the above five factors by using the Eigenvector method are as follows:

$$W = [0.22 \quad 0.57 \quad 0.11 \quad 0.03 \quad 0.07]^T$$

b) Calculation of deterministic matrix

Here, [Case 1](#) was used to demonstrate the calculation of the deterministic matrix. The ternary operator (E_x, E_n, H_e) was obtained according to [Eqs. \(14\)-\(16\)](#) ([Fig. 4](#)). By substituting E_x , E_n , and H_e into the normal cloud generator shown in [Section 3.1](#), the deterministic matrix of [Case 1](#) was obtained:

$$D = \begin{bmatrix} 0.00 & 0.00 & 0.57 & 0.01 \\ 0.00 & 0.00 & 0.02 & 0.11 \\ 0.00 & 0.23 & 0.00 & 0.00 \\ 0.32 & 0.00 & 0.32 & 0.00 \\ 0.10 & 0.24 & 0.05 & 0.00 \end{bmatrix}$$

In order to calculate the deterministic matrix, we need to determine the total number of sampling. Let's take d_{23} and d_{32} as examples, [Fig. 5](#) shows that the values of d_{23} and d_{32} vary with N . It can be seen from [Fig. 5](#) that d_{23} tends to converge when $N = 1.2 \times 10^4$; When $N = 1 \times 10^4$, the result of d_{32} tends to converge. Therefore, N was taken as 1.5×10^4 in this paper.

c) Calculation of membership matrix and classification of rockburst

The membership matrix of [Case 1](#) can be obtained by using [Eq. \(17\)](#):

$$M = W' D = \begin{bmatrix} 0.22 & 0.57 & 0.11 & 0.03 & 0.07 \end{bmatrix} \begin{bmatrix} 0.00 & 0.00 & 0.57 & 0.01 \\ 0.00 & 0.00 & 0.02 & 0.11 \\ 0.00 & 0.23 & 0.00 & 0.00 \\ 0.32 & 0.00 & 0.32 & 0.00 \\ 0.10 & 0.24 & 0.05 & 0.00 \end{bmatrix} \\ = \begin{bmatrix} 0.02 & 0.04 & 0.15 & 0.06 \end{bmatrix}$$

according to [Section 3.2](#), the liability class of [Case 1](#) is III.

The membership vectors of all cases were listed in [Table 5](#). Violent rockburst may occur in Jinping I# tunnel and Qinling railway tunnel, moderate rockburst may occur in the other cases. The error rate is 0% by comparing the predicted class with the field status.

It can be seen from the above calculation process that the proposed model is simple in calculation and can obtain accurate results, which can be used as an auxiliary tool for

engineers to quickly predict rockburst liability.

5 Discussions

a) Compare the proposed AHP with the original AHP

Considering the judgment errors of decision-makers, the proposed AHP revised the PCM according to the Bayesian theory, which is the advantage of the new AHP compared with the original AHP. In addition, the weight obtained based on the new AHP is more reasonable than the original AHP, which can be represented by a quantitative index (i.e., Euclidean distance (ED)).

ED represents the total distance between all elements in the PCM and related ratios of the weights, which can be denoted as (Golany and Kress 1993)

$$ED = \left[\sum_{i=1}^n \sum_{j=1}^n (a_{ij} - w_i/w_j)^2 \right]^{1/2} \quad (18)$$

ED measures both the accuracy of the solution and the reasonableness of the ranking order. The smaller the ED , the more reasonable the weight.

The results of the proposed AHP and the original AHP were shown in Fig. 6. The ED of the new AHP is 1.729, while the ED of the original AHP is 1.738, which indicating that the new AHP is more reasonable than the original AHP. The error rate of the cloud model based on the original AHP is 1/9.

b) Compare the proposed model with the TOPSIS model

Technique for order preference by similarity to an ideal solution (TOPSIS) is one of the commonly used methods in multi-criteria decision-making problems (Wu et al., 2019). In TOPSIS, the positive ideal solution and the negative ideal solution were firstly obtained from Table 3, and then the Euclidean distance between each case and the positive/negative ideal

solution can be calculated. Finally, the dimensionless distance was obtained to predict rockburst liability class.

Fig. 7 reports the comparison between the proposed model and the TOPSIS model for the 9 cases in Section 4. As shown in Fig. 7, the error rate of the TOPSIS model is 1/9. The predicted results are sensitive to the distance function in the TOPSIS model, so the distance function needs to be carefully selected. The proposed model is superior to the TOPSIS model in simplicity and effectiveness.

In summary, the proposed model has a good application prospect in the prediction of rockburst liability.

c) Limitations of the present work

Classification criteria are the basis of multi-criteria decision-making approach or multi-criteria machine learning approach (Classification criteria are not necessary when using the two-class machine learning method (Pu et al., 2019; Li et al., 2021)) for rockburst liability prediction. However, there are no unified classification criteria at present. Different classification criteria can lead to inconsistent results (e.g., Wang et al., 2015; Xu et al., 2018; Xue et al., 2019). In future studies, it is feasible to introduce multiple classification criteria considering the uncertainty of classification criteria to predict rockburst liability.

In addition, the proposed AHP is still a subjective weighting method. It is meaningful to combine the proposed AHP with objective weighting methods such as entropy weighting method to calculate the combination weight.

6 Conclusions

In this paper, five factors (strength-stress ratio, Russenes criterion, brittleness index,

strain energy storage index, and integrity index) were used to construct the standard of rockburst liability. A novel analytic hierarchy process was proposed to determine the weight of these factors, and a cloud model based on the new analytic hierarchy process was proposed for rockburst liability prediction. The conclusions were drawn as follows:

(1) The proposed analytic hierarchy process made full use of all sample information through Bayesian theory. A quantitative index (i.e., Euclidean distance) shows that the weights obtained by the new analytic hierarchy process are more reasonable than those of the original analytic hierarchy process.

(2) The proposed rockburst prediction model (i.e., cloud model based on the novel analytic hierarchy process) accurately predicted the rockburst liability levels of nine actual cases in China. It is suggested that the number of sampling in the proposed cloud model is 1.5×10^4 .

(3) The error rates of the cloud model based on standard analytic hierarchy process and technique for order preference by similarity to an ideal solution are 1/9. The proposed model performs better than the TOPSIS model in terms of simplicity and effectiveness.

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Data Availability

All data generated or analyzed during this study are included within the article.

Declaration of Interest Statement

All authors declare that No conflict of interest exists.

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453 Table 1 A summary of assessment indexes for rockburst prediction

Indicators	Definition	Ref.
Rusenes criterion	σ_{θ}/σ_c	Russebes 1974
Brittleness index	σ_c/σ_t	Wang et al., 1998
Strain energy storage index	W_{et}	Kidybinski 1981
Brittleness index II	$\sigma_c - \sigma_t/\sigma_c + \sigma_t$	Pu et al., 2019
Integrity index	K_V	Hou and Wang 1989
Strength-stress ratio	σ_c/σ_1	Wang et al., 2015
Elastic strain energy density	$\sigma_c^2/2E_s$	Pu et al., 2018

454 Note: σ_{θ} is the tangential stress; σ_c is the uniaxial compressive stress; σ_t is the tensile
455 stress; E_s is the elastic modulus; σ_1 is the major principal stress.

456

457 Table 2 A summary of multi-criteria prediction of rockbursts

Model	Input factors	Ref.	Multi-criteria decision-making method	Machine Learning method
Ideal-point method	Russenes criterion Brittleness index	Xu et al., 2018	✓	
Support vector classifier	Strain energy storage index Tangential stress Uniaxial compressive stress Uniaxial tensile stress Russenes criterion Brittleness index Brittleness index II	Pu et al., 2019		✓
Random forest	Strain energy storage index Tangential stress Uniaxial compressive stress Uniaxial tensile stress Russenes criterion Brittleness index	Dong et al., 2013		✓
Adaptive neuro-fuzzy inference systems	Strain energy storage index Tangential stress Uniaxial compressive stress Uniaxial tensile stress Russenes criterion Brittleness index	Adoko et al., 2013		✓
Fuzzy matter–element model	Strain energy storage index Strength-stress ratio Brittleness index	Wang et al., 2015	✓	
Extension theory	Strain energy storage index Integrity index Uniaxial compressive stress Strength-stress ratio	Xue et al., 2019	✓	
Technique for order preference by similarity to an ideal solution	Strain energy storage index Integrity index Strength-stress ratio Tangential stress	Xue et al., 2020a	✓	
Extreme learning machine	Uniaxial compressive stress Tensile stress Russenes criterion Brittleness index	Xue et al., 2020b		✓
Annular grey target decision-making model	Strain energy storage index Tangential stress Uniaxial compressive stress Uniaxial tensile stress Russenes criterion	Zhou et al., 2019	✓	

Fuzzy comprehensive evaluation	Brittleness index	Pu et al., 2018	✓
	Strain energy storage index		
	Russenes criterion		
	Brittleness index		
Fuzzy comprehensive evaluation model	Strain energy storage index	Wang et al., 1998	✓
	Integrity index		
	Russenes criterion		
	Brittleness index		
	Strain energy storage index		

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460 Table 3 Rockburst liability standard (Zhang et al., 2011)

Input factors	I	II	III	IV
Strength-stress ratio	<0.15	0.15~0.20	0.20~0.40	>0.40
Russenes criterion	<0.20	0.20~0.30	0.30~0.55	>0.55
Brittleness index	<15	15~18	18~22	>22
Strain energy storage index	<2.0	2.0~3.5	3.5~5.0	>5.0
Integrity index	<0.55	0.55~0.60	0.60~0.80	>0.80

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463 Table 4 Typical rockburst cases in China (Wang et al., 1998; Xu et al., 2018)

Cases	Strength- stress ratio	Russenes criterion	Brittleness index,	Strain energy storage index	Integrity index
1	0.37	0.67	12	3.5	0.53
2	0.45	0.82	18.46	3.8	0.76
3	0.29	0.34	23.97	6.6	0.75
4	0.2	0.4	16.49	9	0.75
5	0.26	0.91	16.43	7	0.75
6	0.26	0.8	8.06	7.27	0.75
7	0.17	0.33	24.56	5	0.8
8	0.22	0.53	15.04	9	0.8
9	0.37	0.31	22.86	5	0.75

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466 Table 5 Calculated results of the proposed model

Cases	m_1	m_2	m_3	m_4	Prediction	Field
1	0.02	0.04	0.15	0.07	III	III
2	0.00	0.02	0.14	0.37	IV	IV
3	0.00	0.03	0.61	0.07	III	III
4	0.00	0.18	0.67	0.04	III	III
5	0.00	0.11	0.24	0.55	IV	IV
6	0.11	0.00	0.31	0.24	III	III
7	0.00	0.24	0.36	0.10	III	III
8	0.00	0.06	0.38	0.04	III	III
9	0.00	0.12	0.41	0.01	III	III

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Fig. 1 Some accidents induced by rockbursts (Liang et al., 2019)

Fig. 2 A cloud with $E_x=50$, $E_n=10$, and $H_e=1$

Fig. 3 Flow chart of cloud model based on a novel analytic hierarchy process

478

Factors:

0.1	0.175	0.3	0.6	F_1
0.1	0.25	0.425	0.95	F_2
8	16.5	20	25	F_3
1	2.75	4.25	9	F_4
0.5	0.575	0.7	0.99	F_5
Class:	I	II	III	IV

479

480 (a)

Factors:

0.017	0.017	0.067	0.067	F_1
0.033	0.033	0.083	0.133	F_2
2.333	1	1.333	1	F_3
0.333	0.5	0.5	1.333	F_4
0.017	0.017	0.067	0.063	F_5
Class:	I	II	III	IV

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482 (b)

Factors:

0.01	0.01	0.01	0.01	F_1
0.01	0.01	0.01	0.01	F_2
0.01	0.01	0.01	0.01	F_3
0.01	0.01	0.01	0.01	F_4
0.01	0.01	0.01	0.01	F_5
Class:	I	II	III	IV

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484 (c)

485 Fig. 4 E_x (a), E_n (b), and H_e (c)

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Fig. 5 d_{23} and d_{32} vary with N

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