



Rockburst Prediction of Multi-dimensional Cloud Model Based on Improved Hierarchical and Critic

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Abstract. In high terrestrial stress regions, rockburst is a major geological disaster influencing underground engineering construction significantly. How to carry out efficient and accurate rock burst prediction remains to be solved. Comprehensively consider the objective information of the index data and the important role of subjective evaluation and decision-making in rockburst prediction, and use the improved analytic hierarchy process and the CRITIC method based on index correlation to obtain the subjective and objective weights of each index, and obtain comprehensive weights based on the principle of minimum discriminant information. The original cloud model and the classification interval of the forecast index were modified to make up for the lack of sensitivity of the original cloud model to the average of the grade interval. A hierarchical comprehensive cloud model of each index was generated through a cloud algorithm. Finally, the reliability and effectiveness of the model were verified through several sets of rockburst examples, and compared with the entropy weight-cloud model, CRITIC-cloud model and set pair analysis-multidimensional cloud model. The results show that the model can describe various uncertainties of interval-valued indicators, quickly and effectively determine rockburst severity.

Keywords: Rockburst · Prediction · Analytic hierarchy process · CRITIC method · Multidimensional cloud model

1 Introduction

With the continuous development of tunnels and underground engineering, rock bursts are sudden, difficult to control and highly destructive, which seriously threatens the lives of workers, delays construction periods and causes huge economic losses. It has become a major problem urgently to be solved in international deep mining engineering and underground space development engineering, and it is urgent to find a more effective method for rockburst prediction.

Rockburst prediction includes long-term prediction before construction and short-term prediction of construction process. Short-term prediction generally uses micro-seisms [1], infrared radiation [2], acoustic emission [1, 2], and ultrasonic methods to

make real-time early warning of the exact location and time of rockburst. Among them, microseisms and acoustic emissions are most commonly used in engineering. The macro-prediction of the existence and intensity level of rockburst before construction has guiding significance for the feasibility study stage of the project. The long-term prediction methods are mainly theoretical analysis and prediction. At present, the commonly used processing methods include mathematical comprehensive processing analysis method, model test verification method, and numerical simulation analysis verification method. Among them, the mathematical comprehensive processing analysis method has achieved good prediction results in rockburst prediction and has been successfully applied to practical engineering, such as fuzzy mathematical comprehensive evaluation method [3], generalized artificial neural network [4], particle swarm algorithm [4], Probabilistic Neural Network [5], Support Vector Machines [6, 7], Decision Tree [7], Multilayer Perceptron (MLP) [7, 8], K-Nearest Neighbor (KNN) [7, 8], Rough Set Theory [9], cloud model [9, 12], etc. It should be noted that different criteria and theoretical analysis methods have their own limitations, such as the slow convergence rate of artificial neural networks; the comprehensive evaluation method of fuzzy mathematics cannot reflect the randomness of the system, and the distance discrimination method is highly dependent on samples.

In terms of weight assignment, the expert-based subjective weighting method has obvious shortcomings due to the complex factors affecting the rockburst mechanism and has not yet formed a perfect system; The objective weighting method does not consider the correlation between indicators, and ignores the role of subjective decision-making in practical applications; The analytic hierarchy process is too subjective and may not satisfy the judgment matrix. The single weight assignment cannot accurately measure the influence of various factors, which makes the prediction result deviate from the actual result, and the combination weight lacks the corresponding basis. The cloud model has certain advantages for rockburst prediction due to its ambiguity and randomness. However, with the increase of indicators, the calculation process of the one-dimensional cloud model is complicated, and it cannot reflect the interaction between multiple factors.

This paper adopts a combination weighting method combining improved analytic hierarchy process and CRITIC (Criteria Importance Through Intercriteria Correlation) method based on index correlation, and combines subjective and objective weights to obtain combined weights based on the principle of minimum discriminant information. Make full use of subjective and objective factors to make empowerment more reasonable; The multi-dimensional cloud model is used to predict the rockburst level, which reflects the comprehensive influence of various indicators and simplifies the calculation process of the model. The original cloud model and the classification interval of the predictive indicators were modified to make up for the lack of sensitivity of the original cloud model to the mean of the grade interval. Finally, the established model is used to verify the reliability of the model in the application of rockburst examples in related literature.

2 Combination Empowerment

2.1 Improved Analytic Hierarchy Process

This paper uses the scale construction method to construct the judgment matrix, thereby improving the subjective weight calculation of AHP and avoiding the consistency check. The judgment matrix $R = [r_{ij}]$ satisfies the following conditions: 1) $r_{ij} > 0$; 2) $r_{ii} = 1$; 3) $r_{ij} = \frac{1}{r_{ji}}$; 4) $r_{ij} = r_{ik}r_{kj}$. r_{ij} is the scale value of the first indicator relative to the j -th indicator. The meaning of the standard values is shown in Table 1.

Table 1. Meaning of scale values

| Scale value | Meaning | Scale value | Meaning |
|-------------|--------------------|-------------|----------------------|
| 1.0 | Equally important | 1.6 | Obviously important |
| 1.2 | Slightly important | 1.8 | Absolutely important |
| 1.4 | Strongly important | | |

There are n indicators x_1, x_2, \dots, x_n , subjectively rank the indicators according to the principle of undiminished importance, determine the scale value and record the corresponding scale as t_i . Other elements in the judgment matrix are obtained according to the degree of transitivity, and then the final judgment matrix R is:

$$R = \begin{bmatrix} 1 & t_1 & t_1 t_2 & \cdots & \prod_{i=1}^n t_i \\ \frac{1}{t_1} & 1 & t_2 & \cdots & \prod_{i=2}^{n-1} t_i \\ \frac{1}{t_1 t_2} & \frac{1}{t_2} & 1 & \cdots & \prod_{i=3}^{n-1} t_i \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\prod_{i=1}^n t_i} & \frac{1}{\prod_{i=2}^{n-1} t_i} & \frac{1}{\prod_{i=3}^{n-1} t_i} & \cdots & 1 \end{bmatrix}$$

α_i is the weight value of the i -th index; $\prod_{j=1}^n r_{ij}$ represents the product of all elements in the i -th row of the matrix R . From this, the subjective weight of each indicator in the rockburst prediction can be quantitatively determined as:

$$\alpha_i = \left(\prod_{j=1}^n r_{ij} \right)^{\frac{1}{n}} / \sum_{i=1}^n \left(\prod_{j=1}^n r_{ij} \right)^{\frac{1}{n}} \tag{1}$$

2.2 CRITIC

The CRITIC method is an objective weighting method based on evaluation indicators. It takes into account the comparative strength of the sample and the conflict between the indicators, and the calculation results are more objective and reasonable. Suppose there are m samples and n indicators, and x_{ij} represents the value of the j -th evaluation index of the i -th sample. The evaluation matrix can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix}$$

The calculation steps of objective weight are as follows:

1. Normalization of indicators.

The larger and better indicators are:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{2}$$

The smaller and better indicators are:

$$y_{ij} = \frac{x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{3}$$

The normalized matrix Y is calculated.

2. Calculate the mean \bar{x} and standard deviation s :

$$\bar{x}_j = \frac{1}{m} \sum_{i=1}^m x_{ij} \tag{4}$$

$$s_j = \sqrt{\frac{1}{m} \sum_{i=1}^m (x_{ij} - \bar{x}_j)^2} \tag{5}$$

3. Calculate the coefficient of variation:

$$v_j = \frac{s_j}{\bar{x}_j} \tag{6}$$

4. Calculate the correlation coefficient matrix:

$$\rho_{ij} = cov(y_k, y_l) / (s_k s_l) (k = 1, 2, \dots, n; l = 1, 2, \dots, n) \tag{7}$$

ρ_{ij} is the correlation coefficient between the k -th index and the l -th index, and $cov(y_k, y_l)$ is the covariance between the k -th index and the l -th index.

5. Calculate the amount of information contained in the indicator:

$$\eta_j = v_j \sum_{k=1}^n (1 - \rho_{kj})(j = 1, 2, \dots, n) \tag{8}$$

6. Determine the objective weights as:

$$\beta_{ij} = \frac{\eta_j}{\sum_{i=1}^n \eta_j}(j = 1, 2, \dots, n) \tag{9}$$

2.3 Comprehensive Weight

In order to make the comprehensive weight ω_i as close to a and b as possible without biasing any one of them, the comprehensive weight ω_i is obtained according to the principle of minimum discriminant information, and the objective function is [13]:

$$\left\{ \begin{array}{l} \min J(\omega) = \sum_{i=1}^n (\omega_i \ln \frac{\omega_i}{\alpha_i} + \omega_i \ln \frac{\omega_i}{\beta_i}) \\ s.t. \sum_{i=1}^n \omega_i = 1, \omega_i \geq 0(i = 1, 2, \dots, n) \end{array} \right\} \tag{10}$$

Solving this optimization model, the comprehensive weights are:

$$\omega_i = \frac{\sqrt{\alpha_i \beta_i}}{\sum_{j=1}^n \sqrt{\alpha_j \beta_j}} \tag{11}$$

3 Multidimensional Cloud Model

3.1 Multidimensional Cloud Model Definition and Digital Features

A multi-dimensional cloud model definition is introduced on the definition of a one-dimensional cloud model as follows [11]: Let C be a qualitative concept on the quantitative field $U\{X_1, X_2, \dots, X_n\}$. If $x(x_1, x_2, \dots, x_n)$ is a random realization of the concept, the degree of certainty U of x on $\mu(x(x_1, x_2, \dots, x_n)) \in [0, 1]$ is subject to the normal The distribution $x(x_1, x_2, \dots, x_n) \sim N(E_x(E_{x1}, E_{x1}, \dots, E_{xn}))$ satisfies the normal distribution:

$$Ex_j^i = \frac{C_{minj}^i + C_{maxj}^i}{2} \tag{12}$$

$$En = \frac{a_{ij}}{3} \tag{13}$$

$$He = \beta \tag{14}$$

In the formula, C_{maxj}^i and C_{minj}^i represent the maximum and minimum values of the i-th index interval of the jth index; a_{ij} is the width of the left and right half branches connecting the cloud; E_x represents the basic certainty of the qualitative concept, and is the spatial distribution of cloud drops in the universe of discourse. E_n entropy represents the uncertainty measure of qualitative concepts; H_e superentropy represents the uncertainty of entropy, and reflects the degree to which the random variable corresponding to the qualitative concept deviates from the normal distribution.

3.2 Forecast Indicators and Classification

The mechanism of rockburst occurrence is complex and there are many influencing factors. The selection of indicators is very important for the accuracy of prediction results. Based on the existing research results of rockburst [4, 7, 8, 10–12, 14], Considering internal and external factors, $\frac{\sigma_c}{\sigma_t}$, σ_θ/σ_c , w_{et} and k_s are selected as the main evaluation factors.

Tangential stress refers to the force acting on the bearing surface of the rock mass and parallel to the bearing surface. The greater the stress on the rock mass, the easier it is to destroy the rock mass. The ratio of tangential stress to the uniaxial compressive strength of the rock σ_θ/σ_c reflects the strength conditions of the rock mass and determines the lower limit of the energy required to destroy the rock mass.

Professor Lu Jiayou believes that the occurrence of rock bursts and their intensity are related to the nature of the rock mass. The uniaxial compressive strength of the rock reflects the hardness and lithology characteristics of the rock mass. The tensile strength of the rock is the effect of the uniaxial tension of the rock. The maximum tensile stress that can be withstood during failure is reached, and both are important indicators for judging the stability of rock mass engineering. Therefore, the ratio coefficient of $\frac{\sigma_c}{\sigma_t}$ reflects the lithology of the surrounding rock and can further reflect the integrity of the rock mass.

The rock brittleness index w_{et} is an inherent property of the rock when it is damaged under force. It reflects that the rock has a small strain before macroscopic failure under the action of force, and it is all released in the form of elastic potential energy when it is broken. The degree of difficulty of instantaneous fracture of a rock before failure. The more brittle the rock, the greater the possibility of the rock releasing energy. In a rock mass with the same energy level, the greater the rock brittleness index is the energy released in the same time The bigger it is, the greater the impulse generated during the rock ejection process, and the greater the destructive force caused by the rock ejection, which is an important basis for measuring the intensity of rock bursts.

The elastic deformation index k_s represents the ratio of the elastic strain energy accumulated before the rock reaches the maximum ultimate strength during the compressive deformation process and the loss strain energy after unloading, and reflects the rock's ability to store the elastic deformation potential energy, whether rockburst occurs or not The internal dominant factors of its intensity and its magnitude, the greater the internal energy, the greater the ability to destroy the rock mass, and the greater the probability of rock burst ejection damage.

The one-dimensional cloud model requires that indicators follow a normal distribution within infinite intervals. In fact, the measured values of indicators are usually vague and randomly distributed within a finite interval. This may be inconsistent with the actual distribution of the indicators, leading to deviations from the actual results. According to the research work of Wang et al [2] and others and formula (15), the standard interval for predicting rockburst propensity indicators was revised, as shown in Table 2.

$$\begin{aligned} C_{\max}^n &= Ex^{n-1} + (Ex^{n-1} - C_{\min}^{n-2}) \\ C_{\max}^1 &= Ex^2 + (Ex^2 - C_{\min}^3) \end{aligned} \quad (15)$$

Table 2. Modified rockburst tendency prediction index

| Rockburst level | I no rock burst | II weak rock burst | III medium rock burst | IV strong rockburst |
|--------------------------|-----------------|--------------------|-----------------------|---------------------|
| σ_c/σ_t | 40.00–52.2 | 26.7–40.00 | 14.5–26.7 | 0–14.5 |
| σ_θ/σ_c | 0–0.3 | 0.3–0.5 | 0.5–0.7 | 0.7–0.9 |
| w_{et} | 0–2.00 | 2.00–4.00 | 4.00–6.00 | 6.00–8.00 |
| k_S | 0–0.555 | 0.55–0.65 | 0.65–0.75 | 0.75–0.85 |

3.3 Determine Rockburst Level

To determine the level of rockburst:

1. According to the revised prediction index of rockburst propensity (Table 2), substitute the formula (12) to obtain the digital feature Ex of the multi-dimensional cloud model;
2. Find a_j^i according to formulas (16) to (17), substitute it into formula (13), and find the digital feature En . The fixed value of; He is 0.01;

Growth indicator [1]:

$$a_{jleft}^i = Ex_j^i - C_{miny}^{i-1}, a_{jright}^i = C_{maxj}^{i-1} - Ex_j^i \tag{16}$$

Consumption indicators [1]:

$$a_{jleft}^i = Ex_j^i - C_{miny}^{i-1}, a_{jright}^i = C_{maxj}^{i-1} - Ex_j^i \tag{17}$$

3. The obtained En is substituted into formula (19) to generate a random number En' that obeys the normal distribution;

$$E'_n(E'_{n1}, E'_{n2}, \dots, E'_{nn}) \sim N(E_n(E_{n1}, E_{n1}, \dots, E_{nn})) \tag{18}$$

4. According to formula (20), obtain k_j^i and rockburst instance data and substitute formula (21) to obtain a certain degree of membership of the sample;

$$k_j^i = \frac{\ln(\frac{\ln 4}{9})}{\ln \left| \frac{C_j^i - Ex_j^i}{3En_j^i} \right|} \tag{19}$$

In the formula, C_j^i represents C_{maxj}^i or C_{miny}^i

$$\mu^i \left[x^i(x_1^i, x_2^i, \dots, x_n^i) \right] = \exp\left(-\frac{9}{2} \sum_{j=1}^m \left| \frac{x_j^i - Ex_j^i}{3En_j^i} \right|^{k_j^i} \right) \tag{20}$$

5. Repeat the above steps to obtain the membership of each grade of the sample, and determine the rockburst grade according to the principle of maximum membership.

4 Case Analysis

4.1 Rockburst Case

The 31 cases of rockbursts in this paper are all from published articles, 1–12 groups of data come from literature [11], and 13–31 groups of data come from literature [10].

4.2 Determine Weight

Calculating Subjective Weights

According to the improved analytic hierarchy process (AHP) according to Sect. 2.1, combined with the literature [14], the evaluation matrix (in the order of $\frac{\sigma_\theta}{\sigma_c}$, w_{et} , k_s , $\frac{\sigma_c}{\sigma_t}$) of the prediction indicators in Table 2 is:

$$R = \begin{bmatrix} 1 & 1.8 & 1.7 & 1.6 \\ \frac{1}{1.8} & 1 & \frac{1}{1.3} & \frac{1}{1.4} \\ \frac{1}{1.7} & 1.3 & 1 & \frac{1}{1.2} \\ \frac{1}{1.6} & 1.4 & 1.2 & 1 \end{bmatrix}$$

According to formula (1), the final judgment matrix R is:

$$R = \begin{bmatrix} 1 & 1.8 & 1.7 * 1.8 & 1.6 * 1.7 * 1.8 \\ \frac{1}{1.8} & 1 & \frac{1}{1.3} & \frac{1}{1.4} * \frac{1}{1.3} \\ \frac{1}{1.7 * 1.8} & 1.3 & 1 & \frac{1}{1.2} \\ \frac{1}{1.6 * 1.7 * 1.8} & 1.4 * 1.3 & 1.2 & 1 \end{bmatrix}$$

Obtain the subjective weight (in the order of $\frac{\sigma_\theta}{\sigma_c}$, w_{et} , k_s , $\frac{\sigma_c}{\sigma_t}$) according to formula (1) as:

$$\alpha = [0.4994 \ 0.1791 \ 0.1525 \ 0.1690]$$

Calculate Objective Weights

According to the CRITIC method in Sect. 2.2, normalize the sample data (Table 3) (only $\frac{\sigma_c}{\sigma_t}$ is the larger the better), and bring the sample data into formulas (4) to (6) to obtain the average, variance The coefficient of variation is:

$$\bar{x} = [24.1388 \ 0.4506 \ 4.4531 \ 0.6750]$$

$$s = [7.7175 \ 0.1755 \ 1.3942 \ 0.1093]$$

$$v = [0.3197 \ 0.3895 \ 0.3131 \ 0.1619]$$

Table 3. Engineering example data

| Sample | σ_c/σ_t | σ_θ/σ_c | w_{et} | k_s |
|--------|---------------------|--------------------------|----------|-------|
| 1 | 13.20 | 0.58 | 6.3 | 0.79 |
| 2 | 17.50 | 0.45 | 5.1 | 0.68 |
| 3 | 20.90 | 0.39 | 4.6 | 0.65 |
| 4 | 41.00 | 0.20 | 1.7 | 0.50 |
| 5 | 13.20 | 0.66 | 6.8 | 0.82 |
| 6 | 15.00 | 0.53 | 6.5 | 0.70 |
| 7 | 21.70 | 0.42 | 4.5 | 0.67 |
| 8 | 21.70 | 0.39 | 5.0 | 0.73 |
| 9 | 26.90 | 0.44 | 5.5 | 0.78 |
| 10 | 18.50 | 0.81 | 3.8 | 0.68 |
| 11 | 29.40 | 0.41 | 7.3 | 0.64 |
| 12 | 19.70 | 0.38 | 5.0 | 0.69 |
| 13 | 28.40 | 0.38 | 5.3 | 0.58 |
| 14 | 22.30 | 0.66 | 3.2 | 0.88 |
| 15 | 29.73 | 0.37 | 3.5 | 0.68 |
| 16 | 32.77 | 0.42 | 3.0 | 0.71 |
| 17 | 42.73 | 0.28 | 2.2 | 0.49 |
| 18 | 20.13 | 0.49 | 3.8 | 0.91 |
| 19 | 28.77 | 0.38 | 3.0 | 0.70 |
| 20 | 27.52 | 0.72 | 4.3 | 0.73 |
| 21 | 16.55 | 0.69 | 5.7 | 0.90 |
| 22 | 15.50 | 0.42 | 3.2 | 0.62 |
| 23 | 30.12 | 0.58 | 4.5 | 0.64 |
| 24 | 36.42 | 0.22 | 1.8 | 0.46 |
| 25 | 19.35 | 0.62 | 4.50 | 0.88 |
| 26 | 31.20 | 0.57 | 3.15 | 0.58 |
| 27 | 12.36 | 0.65 | 5.41 | 0.91 |
| 28 | 18.75 | 0.59 | 4.20 | 0.84 |
| 29 | 29.70 | 0.73 | 3.82 | 0.70 |
| 30 | 42.30 | 0.37 | 2.75 | 0.36 |
| 31 | 37.35 | 0.37 | 3.08 | 0.66 |

The correlation coefficient matrix is:

$$R = \begin{bmatrix} 1 & -0.5606 & -0.6533 & -0.5166 \\ -0.5606 & 1 & 0.4034 & 0.5850 \\ -0.6533 & 0.4034 & 1 & 0.3603 \\ -0.5166 & 0.5850 & 0.3603 & 1 \end{bmatrix}$$

The objective weights (in the order of $\frac{\sigma_\theta}{\sigma_c}, w_{et}, k_s, \frac{\sigma_c}{\sigma_t}$) according to formulas (8) and (9) are:

$$\beta = [0.3943 \ 0.2612 \ 0.2359 \ 0.1985]$$

Calculate the Overall Weight

According to the principle of minimum information discrimination, substituting α and β into formula (11) to obtain the integrated weight (in the order of $\frac{\sigma_\theta}{\sigma_c}, w_{et}, k_s, \frac{\sigma_c}{\sigma_t}$) is:

$$\omega = [0.4517 \ 0.2032 \ 0.2032 \ 0.1419]$$

4.3 Forecast Model and Results

According to the step of determining the rockburst grade in Sect. 3.3, substitute the rockburst prediction index and grade interval in Table 1. The values of the numerical characteristics Ex, En and k_j^i are shown in Table 3. According to the digital characteristics substituted into the formula (20) to generate each index cloud model, see Fig. 1; According to the above results, the actual measured values of rock burst examples are brought into the constructed model for prediction, and compared with the actual rock burst level, entropy weight-cloud model, Critic-multidimensional cloud model and analysis-multidimensional cloud model. The specific results are shown in Table 4 (Table 5).

The results show that the prediction results in this paper are basically consistent with the actual rockburst grade, and are not much different from the prediction results of other models, indicating that the proposed multi-dimensional cloud model based on the improved hierarchy method and the CRITIC method is reasonable and effective. The improved analytic hierarchy process gives the weight based on the subjectivity of the decision, the CRITIC method gives the weight value based on the data of the rock burst instance, and the integrated weight obtained based on the fusion of the principle of minimum information identification is more reasonable and improves the reliability of the prediction. The multi-dimensional cloud model reflects the uncertainty of rockburst grade prediction with ambiguity and randomness, and is simpler than the one-dimensional cloud model calculation process; The left and right parts of the normal cloud respectively give the characteristic values of the cloud, optimize the characteristic interval of the multi-dimensional cloud model, and increase the prediction accuracy of the cloud model, especially for the first-level rockburst and second-level rockburst.

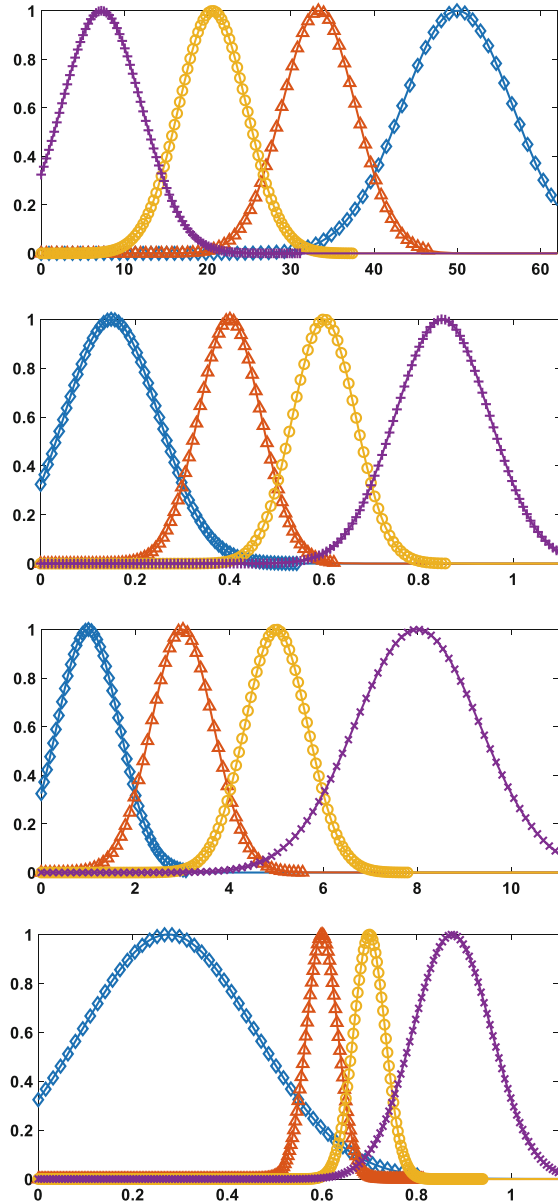


Fig. 1. Rockburst tendency cloud model for each evaluation index

Table 4. Digital characteristics of multidimensional cloud model for rock burst indicators at all levels

| Grade | Index | Ex | En_{left} | En_{right} | He | k_{jleft}^i | k_{jright}^i |
|-------|------------------------------|-------|-------------|--------------|------|---------------|----------------|
| I | $\sigma_{\theta} / \sigma_c$ | 0.15 | 0.00 | 0.117 | 0.01 | 0.00 | 2.208 |
| | σ_c / σ_t | 46.10 | 6.467 | 0.00 | 0.01 | 1.617 | 0.00 |
| | w_{et} | 1.00 | 0.00 | 1.00 | 0.01 | 0.00 | 1.703 |
| | k_s | 0.275 | 0.00 | 0.125 | 0.01 | 0.00 | 6.031 |
| II | $\sigma_{\theta} / \sigma_c$ | 0.40 | 0.133 | 0.100 | 0.01 | 1.349 | 1.703 |
| | σ_c / σ_t | 33.35 | 6.283 | 6.283 | 0.01 | 1.795 | 1.795 |
| | w_{et} | 3.00 | 1.00 | 1.00 | 0.01 | 1.703 | 1.703 |
| | k_s | 0.60 | 0.20 | 0.05 | 0.01 | 0.753 | 1.703 |
| III | $\sigma_{\theta} / \sigma_c$ | 0.60 | 0.10 | 0.10 | 0.01 | 1.703 | 1.703 |
| | σ_c / σ_t | 20.60 | 6.867 | 6.467 | 0.01 | 1.537 | 1.617 |
| | w_{et} | 5.00 | 1.00 | 1.00 | 0.01 | 1.703 | 1.703 |
| | k_s | 0.70 | 0.05 | 0.05 | 0.01 | 1.703 | 1.703 |
| IV | $\sigma_{\theta} / \sigma_c$ | 0.80 | 0.10 | 0.00 | 0.01 | 1.703 | 0.00 |
| | σ_c / σ_t | 7.25 | 0.00 | 6.483 | 0.01 | 0.00 | 1.896 |
| | w_{et} | 7.00 | 1.00 | 0.00 | 0.01 | 1.703 | 0.00 |
| | k_s | 0.80 | 0.05 | 0.00 | 0.01 | 1.703 | 0.00 |

Table 5. Prediction results and comparison of rock burst grade

| Sample | Predicted value of each level | | | | Actual level | Prediction level | Entropy weight-cloud model [11] | Critic-multi-dimensional cloud model [12] | Analysis-multi-dimensional cloud model [10] |
|--------|-------------------------------|--------|--------|--------|--------------|------------------|---------------------------------|---|---|
| | I | II | III | IV | | | | | |
| 1 | 0 | 0.0132 | 0.3658 | 0.4326 | IV | IV | IV | IV | IV |
| 2 | 0.0022 | 0.1090 | 0.6238 | 0.0704 | III | III | III | III | III |
| 3 | 0.0107 | 0.2512 | 0.4872 | 0.0210 | III | III | III | III | III |
| 4 | 0.8819 | 0.2796 | 0.0037 | 0 | I | I | I | I | I |
| 5 | 0 | 0.0065 | 0.2581 | 0.6102 | IV | IV | III-IV* | IV | IV |
| 6 | 0 | 0.0279 | 0.5320 | 0.2273 | III | III | III | III | III |
| 7 | 0.0091 | 0.2723 | 0.5693 | 0.0249 | III | III | III | III | III |
| 8 | 0.0024 | 0.1881 | 0.5300 | 0.0351 | III | III | III | III | III |
| 9 | 0 | 0.2087 | 0.3702 | 0.0268 | III | III | III | III | III |
| 10 | 0 | 0.0577 | 0.4365 | 0.1129 | III | III | III | III | III |
| 11 | 0.0054 | 0.1509 | 0.1676 | 0.0086 | II | II-III* | II | II | II |
| 12 | 0.0041 | 0.1620 | 0.5489 | 0.0358 | III | III | III | III | III |
| 13 | 0.0360 | 0.4433 | 0.2213 | 0.0038 | II | II | II | II | II |
| 14 | 0 | 0.0815 | 0.2768 | 0.0456 | III | III | III | III | III |
| 15 | 0.0541 | 0.7042 | 0.2156 | 0.0025 | II | II | II | II | II |
| 16 | 0.0449 | 0.7453 | 0.1626 | 0.0015 | II | II | II | II | II |
| 17 | 0.7141 | 0.3198 | 0.0055 | 0 | I | I | I | I | I |
| 18 | 0 | 0.0754 | 0.2620 | 0.0372 | III | III | III | III | III |
| 19 | 0.0400 | 0.6599 | 0.2245 | 0.0028 | II | II | II | II | II |
| 20 | 0 | 0.1882 | 0.4646 | 0.0394 | III | III | III | III | III |
| 21 | 0 | 0.0125 | 0.2786 | 0.2988 | IV | IV | IV | IV | IV |
| 22 | 0.0089 | 0.1496 | 0.2697 | 0.0181 | II | III* | III* | III* | III* |
| 23 | 0.0177 | 0.4541 | 0.4021 | 0.0092 | II | II | II | II | II |
| 24 | 0.6896 | 0.3644 | 0.0070 | 0 | I | I | I | I | I |
| 25 | 0 | 0.0472 | 0.4150 | 0.1227 | III | III | III | III | III |
| 26 | 0.0605 | 0.6703 | 0.1910 | 0.0020 | II | II | II | II | II |
| 27 | 0 | 0.0069 | 0.2110 | 0.3228 | IV | IV | IV | IV | IV |
| 28 | 0 | 0.0655 | 0.4803 | 0.1188 | III | III | III | III | III |
| 29 | 0.0028 | 0.2616 | 0.3697 | 0.0170 | III | III | III | III | III |
| 30 | 0.4963 | 0.2371 | 0.0048 | 0 | I | I | I | I | I |
| 31 | 0.1782 | 0.7515 | 0.0651 | 0 | II | II | II | II | II |

5 Conclusion

1. Choose four indexes: the ratio of the maximum principal stress to the rock uniaxial tensile strength σ , the ratio of the maximum tangential stress to the maximum principal stress σ , the rock elasticity index w and the rock integrity coefficient k , and revise the upper limit of the infinite interval of the index, Establish a multi-index forecasting standard for propensity. AHP and CRITIC method are used to obtain subjective weight and objective weight respectively, and the comprehensive weight is obtained according to the principle of minimum identification information.
2. A multi-dimensional cloud model is adopted to establish a graded comprehensive cloud for rockburst propensity prediction. The asymmetric interval in the typical multi-dimensional cloud model is divided into two parts. The data is verified by 31 sets of rockburst engineering examples. The rationality and effectiveness of propensity forecasting, compared with other forecasting methods, shows the applicability of this model.
3. Compared with other methods, the cloud model can reflect the uncertainty of multi-index forecasting and visually display the forecasting process. The establishment process of the one-dimensional cloud model is complicated and the calculation time is long, but the establishment process of the multi-dimensional cloud model is simple, the calculation time is short, and the prediction results are more accurate; the selection of the digital features of the multi-dimensional cloud model is conducive to improving the accuracy of rockburst prediction and the impact. The index division of rockburst grading can further improve the cloud model for rockburst prediction, and the prediction result will be more in line with reality.

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