A Rockburst Proneness Evaluation Method Based on Multidimensional Cloud Model Improved by Control Variable Method and Rockburst Database

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Rockbursts are common geological disasters in underground engineering, and rockburst proneness evaluation is an important research subject. In this study, a multidimensional cloud model was used to evaluate the rockburst proneness level, and the control variable method was used to establish 15 multidimensional cloud (MC) models. The key factors affecting the accuracy of multidimensional cloud model evaluation are numerical characteristics, weight, and normalization methods. The optimal numerical characteristics calculation method of a multidimensional cloud model was determined, and an improved CRITIC (IC) weight method was optimised by introducing the relative standard deviation and an improved quantisation coefficient. Six rockburst indexes were used as input for the multidimensional cloud model, including the elastic deformation energy index $W_{el}$, maximum tangential stress $\sigma_{\theta}$ (MPa) of a cavern, uniaxial compressive strength $\sigma_c$ (MPa), uniaxial tensile strength $\sigma_t$ (MPa), strength brittleness coefficient $B_1 = \sigma_c/\sigma_t$, and stress coefficient $\sigma_{\theta}/\sigma_c$. The model was used to learn 271 groups of complete rockburst cases, and the MC-IC rockburst proneness evaluation method was established. The performance of the proposed MC-IC rockburst proneness method was verified by an 8-fold cross-validation and confusion matrix (precision, recall, F1). The method was tested to evaluate 20 groups of rockburst cases from the Jiangbian Hydropower Station, and the accuracy reaches 95%. The evaluation results were compared with three empirical criteria: four cloud-based methods, three unsupervised learning methods, and four supervised learning methods; the accuracy of the method established in this paper is 93.33%. The results showed that the MC-IC method had an excellent performance in evaluating rockburst proneness and can provide a practical basis for identifying rockburst hazard areas in deep engineering.

1. Introduction

Rockburst is one of the most severe geological disasters in deep diversion tunnels, the deep mining of metal mines, underground water-sealed oil storage caverns, and the deep burial treatment of nuclear waste. A rockburst is a sudden collapse of a surrounding rock mass accompanied by violent shock waves that quickly releases enormous amounts of energy. It has the characteristics of instantaneity and strong destructive power [1–3] and poses a significant threat to personnel safety and equipment. Domestic and home scholars take experiments in the lab and microseismic monitoring in sites to reveal the mechanism of rockburst [4–9]. Peng et al. [10] revealed the influence of confining pressures on deformation characteristics of sandstones by cyclic loading and unloading tests. Tao et al. [11, 12] obtained the dynamic stress concentration around the hole from the perspective of wave theory and the dynamic stress concentration and the initial stress superposition of original rocks for the first time caused by dynamic perturbation scattering through the combined dynamic and static action test device and proved that this is the main reason for the occurrence of rockburst around the chamber. Feng et al. [13, 14] researched the fracture mechanics behaviour of sandstone, revealing the microscopic mechanism of the change of fracture characteristics of thermally damaged sandstone. Ren et al. [15]
studied cracking mechanisms during schist strain burst by moment tensor analysis. Gong et al. [16] first discovered the linear energy storage law during rock loading, proposed a residual elastic energy index to evaluate rockburst tendency. Liu et al. [17] revealed the evolutionary process of structure-type rockburst by a real-time microseismic (MS) monitoring system. Owing to the complexity and uncertainty of rockburst, it is difficult to disclose the occurrence mechanism of rockburst completely. Evaluating rockburst prone-ness was used to provide a practical basis for identifying rockburst hazard areas and taking countermeasures to prevent and control rockburst in deep engineering.

The methods for rockburst proneness evaluation are mainly divided into four categories: empirical methods, uncertainty theory, unsupervised learning, and supervised learning [18]. There are approximately 100 empirical methods, including the strength brittleness coefficient $B$ method [19], deformation brittleness index KU method [20], improved brittleness index BIM [21], energy storage index $k$ [22], rockburst proneness index Wet [23], impact energy index [24], Russenes criterion [25], and Tao Zhenyu criterion [2]. Other single-index criteria include the multi-factor index criterion [19, 26–28] and the rockburst chart method [29–31]. Recently, Li et al. [32] conducted a full-path scientific analysis of the energy storage characteristics of deep surrounding rock, a high-stress occurrence environment, and mining stress and proposed a rockburst dynamic criterion based on the dynamic and static energy index. The
surrounding rock of underground engineering is a complex geological environment; therefore, empirical indicators cannot comprehensively and accurately evaluate rockburst proneness [33].

With the wide application of mathematical algorithms and machine learning in geotechnical engineering [34–37], supervised learning algorithms are being increasingly used in rockburst proneness evaluation. For example, Feng and Wang [38] used intelligent rock mechanics and artificial neural networks to predict rockbursts in a South African mining area. They achieved good results by selecting the main control factors of rockburst: strength-stress ratio, tension-compression strength ratio, and impact energy index. Shirani Faradonbeh and Taheri [39] used six indexes including maximum tangential stress, uniaxial compressive strength, uniaxial tensile strength, and elastic strain energy index to study the effect of the emotional neural network (GA-ENN), gene expression programming (GEP), and decision-tree-based C4.5 algorithm in rockburst proneness evaluation. It was concluded that the GEP and GA-ENN methods have a higher evaluation accuracy. Adoko et al. [40] used a fuzzy inference system and an adaptive neural fuzzy inference system combined with field-measured data to predict the level of rockburst proneness.

An unsupervised learning algorithm was applied in the study of rockburst proneness evaluation. For example, Zhou and Gu [41] established a fuzzy self-organising neural network model based on geographic information system technology and evaluated rockburst proneness in deep lead–zinc mining. Gao [42] introduced the bionic clustering optimisation method, an ant clustering algorithm, for rockburst prediction for the first time. Chen et al. [43] established a new rockburst proneness evaluation method using hierarchical clustering analysis and a complete correlation method. They evaluated and verified the rockburst proneness of the Jinping II hydropower station.

In addition, uncertainty theory has been gradually applied to the evaluation of rockburst proneness. Wang et al. [19] selected the main controlling factors affecting rockbursts—in situ stress, tensile and compressive strength, and elastic energy index—and used the fuzzy mathematics comprehensive evaluation method to evaluate the rockburst intensity of underground projects, and the results were consistent with an actual situation. Yu et al. [44] aimed to address the problem of frequent rockbursts in a mining area using nine decision factors including structural plane type, mining method, and support type. The rockburst decision system was established by introducing a rough set and genetic algorithm. To evaluate rockburst proneness, Li and Du [45] applied fuzzy theory and mathematical statistics, a cloud model using qualitative knowledge, to describe the uncertain transformation between a qualitative concept and its quantitative representation. Li et al. [46] proposed a rockburst evaluation method combining the grey correlation method, principal component analysis, and cloud theory to evaluate the rockburst proneness of the Jiangbian Hydropower Station. Liu et al. [47] established an attribute weight-cloud model. Zhou et al. [48] established the entropy weight-cloud model, and Zhang et al. [49] established a rockburst cloud model based on index distance and uncertainty measurements. Their research results achieved good results in the evaluation of rockburst proneness. However, for rockburst proneness evaluation based on the cloud model, most of the research of domestic and home scholars are only focused on building a new rockburst proneness evaluation method. The influence of numerical characteristics, weight, and normalization methods on the evaluation results has not been studied. Only a few studies have been performed on improving the weight method. Therefore, a rockburst proneness evaluation method is proposed based on a multidimensional cloud model improved by the control

Figure 3: Factors and their combinations that affect the evaluation accuracy of multidimensional cloud model.
variable method and rockburst database. First, a multidimensional cloud model and a rockburst database were established. Second, the factors affecting the accuracy of the rockburst proneness evaluation of the model were studied using the control variable method. Subsequently, a rockburst proneness evaluation method was established based on a multidimensional cloud model improved by the control variable method and database. Finally, the method was verified using 20 groups of rockburst cases from the Jiangbian Hydropower Station. In addition, the evaluation results were compared with typical empirical criteria, unsupervised learning, and supervised learning methods.

2. Multidimensional Normal Cloud Model and Weight Determination Method

2.1. Multidimensional Normal Cloud. The cloud model theory was proposed by Li and Du [45] based on fuzzy theory and mathematical statistics, which uses linguistic value (qualitative knowledge) to describe the uncertainty transformation model between a qualitative concept and its quantitative representation. It is defined as \( U \), a quantitative domain expressed by exact numbers, and \( C \) is a qualitative concept of \( U \). If the quantitative value \( x \in U \), where \( x \) is a random realisation of the qualitative concept \( C \), the degree of certainty of \( x \) to \( C \) is a random number, and \( \mu : U \rightarrow [0, 1] \), \( \forall x \in U, x \rightarrow \mu(x) \). Then, the distribution of \( x \) on \( U \) is called a cloud, and each \( x \) is called a cloud drop. The realisation of the cloud model is achieved mainly through the establishment of a cloud model generator that includes a forward (Figure 1(a)) and a backward cloud generator (Figure 1(b)).

The multidimensional normal forward cloud model is a transformation of a qualitative concept to a quantitative representation; that is, the process of cloud droplets generated by the numerical characteristics of a cloud. The definition is as follows:

Let \( U\{x_1, x_2, \ldots, x_m\} \) be an \( m \)-dimensional quantitative domain represented by exact values, of which \( C \) is a qualitative concept. If the quantitative values \( x \in U \) and \( X\{x_1, x_2, \ldots, x_m\} \) are random realisations of the qualitative concept \( C \), then \( X\{x_1, x_2, \ldots, x_m\} \) satisfy

\[
X\{x_1, x_2, \ldots, x_m\} \sim N\left(\text{Ex}(E_1, E_2, \ldots, E_m), (\text{He}(H_1, H_2, \ldots, H_m))^2\right),
\]

where \( E_x = (E_1, E_2, \ldots, E_m) \sim N(\mu_x, \sigma_x^2) \), \( (\text{He}(H_1, H_2, \ldots, H_m))^2 \) and the certainty degree of \( X\{x_1, x_2, \ldots, x_m\} \) to \( C \) is \( \mu(x(1, x_2, \ldots, x_m)) \in [0, 1] \) and satisfies

\[
\mu(x) = e^{-\sum_{j=1}^{n} \left( (x_j - \text{Ex}_j)^2 / 2 \left( \text{En}_j \right)^2 \right)} \quad j = 1, 2, \ldots, m.
\]

The distribution of \( X\{x_1, x_2, \ldots, x_m\} \) on \( U\{x_1, x_2, \ldots, x_m\} \) is called an \( m \)-dimensional normal cloud, \( \text{Ex} \) is the expectation, \( \text{En} \) is the entropy, and \( \text{He} \) is the hyperentropy.

The multidimensional normal backward cloud model is a transformation model that realises the transformation from quantitative values to qualitative concepts. It can convert a specific amount of data into qualitative concepts represented by numerical characteristics (Ex, En, He). The implementation process is based on the statistical principle of a backward normal cloud generator. There are two types of generator algorithms: one requires the use of certainty information, and the other does not. For the former, it is difficult to give or obtain the value of certainty in practical applications, particularly when the algorithm is extended to multiple dimensions, and the multidimensional backward cloud model will have a greater error in calculation results than the one-dimensional backward cloud model [45]. For the latter, operability is strong, and it only needs sample point inputs and outputs numerical characteristics representing qualitative concepts through backward cloud generators without certainty information.

2.2. Implementation Procedure. The steps to establish a multidimensional cloud model for rockburst proneness evaluation are shown in Figure 2.

Step 1. Establish rockburst instance data set, select rockburst proneness evaluation index, and determine rockburst level.

Step 2. Check abnormal data by boxplot, and divide MS (modeling sets) and TS (test sets) by an 8-fold method.

Step 3. Compute numerical characteristics of multidimensional cloud model.

Step 4. Calculate the weight of \( m \) rockburst proneness evaluation indexes.

Step 5. Generate the cloud model considering \( l \) rockburst grades and \( m \) indexes using a multidimensional normal cloud generator.
Step 6. Calculate the membership degree using the test sets TS combined with the index weight of rockburst proneness evaluation, cloud model of rockburst levels, and indexes. Based on the principle of maximum membership degree, complete the rockburst proneness evaluation of the test set TS as

$$
\mu_k[X(x_1, x_2, \ldots, x_b)] = e^{-\sum_{j=1}^{b} \left( \omega_j (x_j - Ex_j)^2 / 2 \left( En_j' \right)^2 \right)}, \quad j = 1, 2, \ldots, a, \quad k = 1, 2, \ldots, l,
$$

where $\mu_k[X(x_1, x_2, \ldots, x_b)]$ is the degree of certainty that the position belongs to a class $k$ rockburst, $\omega_j$ is the weight of indicator $j$, $x_j$ is the measured value for indicator $j$, $Ex_j$ is the expectation of the $j$ index belonging to a class $k$ rockburst, and $En_j'$ is a normal random number for indicator $j$. Here, $a = 6$, and $l = 4$.

Step 7. Judge whether the numerical characteristics, weight, and normalization methods of the critical factors affected the accuracy. If the accuracy was not affected, use the model built in Step 6. If the accuracy was affected, continue to Step 8.

Step 8. Determine the best numerical characteristics method and improve other vital factors (weight method and normalization method).

Step 9. Establish rockburst proneness evaluation method MI-IC.

2.3. Scheme of Parameter Sensitivity Test for Evaluation Model. Three numerical characteristics determination methods, three weight determination methods, and three normalization methods were selected. Combined with the rockburst dataset and based on the accuracy of the evaluation results, the optimal combination of the above three factors and the multidimensional cloud model was studied. A total of 15 combinations were formed as shown in Figure 3. For example, in the B1-Q1-S1 method, B1 represents normalization method 1, Q1 represents weight method 1, and S1 represents numerical characteristics method 1.

2.3.1. Determination of Weight Method. Weight determination is very important in the evaluation of rockburst proneness. The reasonableness of the determination of weight distribution is directly related to the rationality and reliability of the evaluation results [36].

Commonly used weight determination methods include subjective weighting method, objective weighting method, and a combination of the two. Subjective weighting methods mainly include the analytic hierarchy process, expert estimation method, binomial coefficient method, and ring ratio scoring method. When using these methods to determine index weight, experts or decision-makers require rich empirical knowledge, and this method uses strong subjectivity unsuitable for general engineering applications. The combined weighting method combines the subjective and objective weighting methods according to specific mathematical methods but still has the shortcomings of the subjective weighting method. This study was based on the entropy weight method, CRITIC method, and dynamic weighting method based on index distance and uncertainty. The entropy weight method [50] uses the entropy theory method to determine the weight of each index. The dynamic weighting...
method based on index distance and uncertainty measurement constructs the mass function for the measured values of different indices through a ridge function. It determines the index weight by considering the multievidence relationship coefficient of the Jousselme distance [36]. The CRITIC method was proposed by Diakoulaki et al. [51] to comprehensively measure the objective weight of indicators by combining the information content of evaluation indicators and the correlation between indicators. The calculation process for the CRITIC method entails the following seven steps.

Step 1. Construct matrix $A = (a_{ij})_{m \times n}$ using the $m$ objects to be evaluated and $n$ evaluation indexes, where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$.

Step 2. Calculate the normalized matrix $A$.

Step 3. Calculate the standard deviation $\sigma_j$ of the $j$-th criterion.

Figure 6: Histogram for the six parameters considered to evaluate the rockburst proneness.
Table 2: Statistical features of the rockburst databases.

| Parameter          | Mean   | Standard deviation | Maximum   | Minimum   |
|--------------------|--------|--------------------|-----------|-----------|
| \( \sigma_{0} (\text{MPa}) \) | 61.86  | 54.13              | 297.80    | 2.60      |
| \( \sigma_{1} (\text{MPa}) \) | 116.90 | 50.91              | 306.58    | 18.32     |
| \( \sigma_{r} (\text{MPa}) \) | 7.75   | 4.82               | 22.60     | 0.38      |
| \( \sigma_{0}/\sigma_{r} \) | 0.57   | 0.64               | 4.87      | 0.05      |
| \( \sigma_{r}/\sigma_{r} \) | 20.11  | 13.91              | 80        | 0.15      |
| \( W_{t} \) | 5.20   | 4                  | 30        | 0.81      |

Step 4. Calculate the correlation coefficient using the standardized matrix \( A \ast \) using Equation (4).

\[
X = (r_{kl})_{m \times n}, \ k = 1, 2, \cdots n, \ j = 1, 2, \cdots n, \text{ and } r_{ki} \text{ is the correlation coefficient between index } k \text{ and index } l.
\]

\[
r_{kl} = \frac{1}{n} \sum_{i=1}^{n} (a_{ik} - \overline{a}_{k})(a_{il} - \overline{a}_{l}) = \frac{1}{\sqrt{\sum_{i=1}^{n} (a_{ik} - \overline{a}_{k})^2 \sum_{j=1}^{n} (a_{il} - \overline{a}_{l})^2}}
\]

Step 5. Calculate the quantitative coefficient of independence of each evaluation index as

\[
\eta_{j} = \sum_{k=1}^{n} (1 - r_{kj}), \ j = 1, 2, \cdots, n.
\]

Step 6. Calculate the quantisation coefficient of comprehensive information and degree of independence of each index as

\[
C_{j} = \sigma_{j} \eta_{j}.
\]

Step 7. Determine the weights of evaluation indicators as

\[
\omega_{j} = C_{j} \sum_{j=1}^{n} C_{j}, \ j = 1, 2, \cdots, n.
\]

2.3.2. Determination of Numerical Characteristics

(1) Numerical Characteristic Determination Method 1. The multi-index evaluation criteria for rockburst proneness mainly calculate the first numerical characteristics. The numerical characteristics obtained by this method were independent of the rockburst data and were calculated by the following a four-step procedure.

Step 1. Establish a rockburst proneness judgment standard composed of multiple indicators as shown in Table 1.

Step 2. Determine the expectation \( \text{Ex} \). Suppose there is a specific variable \( A \), and its value range is \( A \{X_{\text{min}}, X_{\text{max}}\} \), then \( \text{Ex} \) is calculated as

\[
\text{Ex} = \frac{(X_{\text{min}} + X_{\text{max}})}{2}, \tag{8}
\]

where \( X_{\text{min}} \) and \( X_{\text{max}} \) represent the maximum and minimum boundary values of variable \( A \), respectively.

Step 3. Determine the entropy \( \text{En} \). \( \text{En} = \text{Ex}_{\text{max}}/3 \), where \( \text{E} \) \( X_{\text{max}} \) represents the maximum expected value of each rockburst grade as an evaluation parameter.

Step 4. Determine the hyperentropy \( \text{He} \), where \( 0.01 \leq \text{He} \leq 0.5 \), and its value is directly proportional to \( \text{En} \).

(2) Numerical Characteristics Determination Method 2. The numerical characteristics of multidimensional normal backward cloud models with different indices and grades [47] were calculated as

\[
\begin{aligned}
E_{x} &= \frac{1}{n} \sum_{i=1}^{n} x_{i}, \\
E_{n} &= \frac{\text{max}(X) - \text{min}(X)}{6}, \\
\text{He} &= k,
\end{aligned}
\]

where \( x_{i} \) is the rockburst data value of a specific index, \( N \) is the group number of rockburst data, and \( k \) is a constant directly proportional to \( \text{En} \).

(3) Numerical Characteristics Determination Method 3. The third numerical characteristic is constructed by the training set and multidimensional normal backward cloud generator [45, 51] obtained as

\[
\begin{aligned}
E_{x} &= \frac{1}{n} \sum_{i=1}^{n} x_{i}, \\
E_{n} &= \sqrt{\frac{1}{2n} \sum_{i=1}^{n} |x_{i} - E_{x}|}, \\
\text{He} &= \sqrt{S - E_{n}^{2}}, 0 < \text{He} < \frac{E_{n}}{3},
\end{aligned}
\]

where \( S \) is the second-order central moment of the sample

\[
S = \frac{1}{n - 1} \sum_{i=1}^{n} |x_{i} - E_{x}|.
\]

2.3.3. Normalization Methods

(1) Min-Max Normalization. Min-max normalization performs a linear transformation of the original data and preserves the relationships among the original data values.
Direct indicator is as follows:

\[ a^*_{ij} = \frac{a_{ij} - \text{MIN} a_{ij}}{\text{MAX} a_{ij} - \text{MIN} a_{ij}}, \quad 1 \leq i \leq n; \quad i = 1, 2, \cdots m; \quad j = 1, 2, \cdots n. \]  

\[ (12) \]

Negative indicator is as follows:

\[ a^*_{ij} = \frac{\text{MAX} a_{ij} - a_{ij}}{\text{MAX} a_{ij} - \text{MIN} a_{ij}}, \quad 1 \leq i \leq n; \quad i = 1, 2, \cdots m; \quad j = 1, 2, \cdots n. \]

\[ (13) \]

(2) Z-Score Normalization. The Z-score represents the distance from the mean of the original data measured using the standard deviation. For a Z-score value > 0, X > mean value; for a Z-score value < 0, X > mean value; for a Z-score value = 0, X = mean value; for a Z-score value = 1, X

\[ (12) \]

Figure 7: 3D data distribution graph for three rockburst proneness evaluation indexes in rockburst database: (a) \( \sigma_\theta(MPa) \), \( \sigma_c(MPa) \), \( \sigma_t(MPa) \); (b) \( \sigma_\theta/\sigma_c \), \( \sigma_c/\sigma_t \), \( W_c \).

Figure 8: Correlation heat map of the six parameters.
= sum of mean and standard deviation; and for a Z-score value = −1, X = mean minus standard deviation. The distribution is shown in Figure 4.

The Z-score method is expressed as follows:

\[ a_{ij}^* = \frac{a_{ij} - \bar{a}_j}{s_j}, \quad i = 1, 2, \cdots m; \quad j = 1, 2, \cdots n, \]  

(14)

where

\[ s_j = \sqrt{\frac{1}{a - 1} \sum_{i=1}^{a} (a_{ij} - \bar{a}_j)^2}, \quad \bar{a}_j = \frac{1}{a} \sum_{i=1}^{a} a_{ij}, \]  

(15)

and \( \bar{a}_j \) and \( s_j \) are the mean value and standard deviation of the \( j \)-th index, respectively.

3. Database Setup

3.1. Database Collection. The establishment of the rockburst proneness evaluation model was based on actual field rockburst cases. Therefore, through extensive access to worldwide articles related to rockburst proneness evaluation research, the rockburst database was collected from approximately 20 years of underground engineering cases. The database included 18 data cases from Wang et al. [19], 34 data cases from Liu et al. [52], 132 data cases from Zhou et al. [53], 46 data cases from Dong et al. [54], 174 data cases from Adoko et al. [40], 164 data cases from Liu et al. [47], 246 data cases from Zhou et al. [50], and 135 data cases from Li et al. [55]. A total of 271 groups of fields rockburst data without repetition and missing values were obtained from tunnels, water conservancy sites, hydropower projects, and mines as shown in Table S1. The evaluation indexes of rockburst proneness were selected based on the rockburst proneness index used in the above data and a comprehensive consideration of the factors affecting the occurrence of rockbursts such as energy, stress, and brittleness. The indexes selected included the elastic deformation energy \( W_{et} \), maximum tangential stress \( \sigma_\theta \), uniaxial compressive strength \( \sigma_c \), tensile strength \( B_1 = \sigma_c / \sigma_t \), strength brittleness coefficient \( \sigma_\theta / \sigma_c \), and stress coefficient. The evaluation level of rockburst proneness was divided into four levels: none, light, moderate, and high. Furthermore, \( W_{et}, \sigma_\theta, \) and \( B_1 \) are often used alone as empirical indicators to evaluate rockburst proneness [18, 20, 23].

3.2. Database Description. Through the analysis of the collected rockburst dataset, 19% (52 cases) had a rockburst grade of none, 31% (83 cases) had a light rockburst grade, 32% (88 cases) had a moderate rockburst grade, and 18% (48 cases) had a high rockburst grade (Figure 5). Figure 6 and Table 2 show the histograms, cumulative percentages, and statistics of rockburst databases (such as means, minimum and maximum values, and standard deviations). They show that the data distribution of the rockburst database established in this study had a specific range. The rockburst proneness evaluation indexes \( (\sigma_\theta, \sigma_c, \sigma_t) \) or \( (\sigma_\theta / \sigma_c, \sigma_c / \sigma_t, W_{et}) \) were used as the three axes of the 3D coordinate system to establish a 3D data distribution graph for rockburst proneness evaluation indexes in the rockburst database (Figure 7). As shown in Figure 7, with an increase in the rockburst proneness index values, the rockburst level also increased. When most rockburst occurred, \( \sigma_\theta, \sigma_c, \sigma_t, W_{et} \) were concentrated in the ranges 0-150 MPa, 50-200 MPa, 0-15 MPa, 0-1 MPa, 0-40 MPa, and 0-10 MPa, respectively. High rockbursts occurred when \( \sigma_\theta \) exceeded 150 MPa or \( \sigma_\theta / \sigma_c \) exceeded 2, and the values of the other indexes were not related to the magnitude of the rockburst level.
3.3. Correlation Analysis of Parameters. The correlation coefficient was used to measure the degree of correlation between two variables. It is defined as the covariance of two variables divided by the product of their standard deviations (Equation (4)), and its value range is [-1,1]. A negative correlation is indicated by [-1,0], and (0,1] indicates a positive correlation. An absolute value of correlation coefficient greater than 0.8 is called high correlation, the absolute value of correlation coefficient less than 0.3 is called low correlation, the others are moderately correlated, and the correlation coefficient is proportional to the degree of correlation. The correlation distribution of each rockburst proneness evaluation index in the rockburst database established in this study is shown in Figure 8.

| Rockburst intensity | \(\sigma_0\) (MPa) | \(\sigma_1\) (MPa) | \(\sigma_2\) (MPa) | \(\sigma_\theta/\sigma_c\) | \(W_{d_t}\) |
|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| None                | 0                   | 0                   | 0                   | 0                   | 47.93, 45.90, 47.93 |
| Light               | 148.40              | 263                 | 21.49, 22.60, 22.40 | 0                   | 69.69 |
| Moderate            | 0                   | 256.5, 304.21, 306.58 | 22.6, 20.9 | 1.27 | 49.5, 45.5, 55, 49.5, 50.9, 80, 73.33, 76.67, 78.69, 65.45, 64.23, 66.75, 61.79, 73 |
| Strong              | 225.5, 225.5, 225.5, 225.5, 274.3, 274.3, 274.3, 297.8, 297.8, 157.3, 167.2 | 304.2 | 22.6, 20.9 | 1.26, 2.61, 3.69, 2.27, 2.47, 3.18, 4.49, 2.77, 3, 3.45, 4.87, 3, 3.26 | 20, 30, 30, 30, 21, 21, 21, 21, 21, 21 |

3.4. Outlier Detection. The boxplot method detects data by using the maximum, minimum, median, first quartile, and third quartile of a dataset without requiring data distribution. This method defines an abnormal value as a data value less than \(X_{ss} - 1.5D_d\) or greater than \(X_{ss} + 1.5D_d\). \(X_{ss}\) represents the lower quartile, which means that the data value in the dataset is less than one-quarter of its value. \(X_{s\theta}\) represents the upper quartile, indicating that the data value in the dataset is greater than one-quarter of its value. \(D_d\) is the difference between the upper quartile \(X_{ss}\) and the lower quartile \(X_{ss}\), which is called the quartile spacing, and contains half of the data. The distribution of abnormal data is shown in Figure 9 and Table 3. After the boxplot method detected abnormal data, 51 groups were abnormal data (68), and 220 groups were normal data.

4. Rockburst Proneness Evaluation Model Based on Multidimensional Cloud Model

4.1. Training Set and Test Set Selection. A “good” machine learning model can provide more accurate prediction results on any dataset and reduce the prediction error. In the process of machine learning, the learner is usually used to learn the data features in the training set, and the test set is used to test its ability to discriminate new samples. The division of the training and test sets should maintain the consistency of the data distribution as much as possible to avoid the impact on the final result owing to the other deviations introduced by the data division process.

Table 3: Rockburst data handle results.

| Rockburst intensity | \(\sigma_0\) (MPa) | \(\sigma_1\) (MPa) | \(\sigma_2\) (MPa) | \(\sigma_\theta/\sigma_c\) | \(W_{d_t}\) |
|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| None                | 0                   | 0                   | 0                   | 0                   | 47.93, 45.90, 47.93 |
| Light               | 148.40              | 263                 | 21.49, 22.60, 22.40 | 0                   | 69.69 |
| Moderate            | 0                   | 256.5, 304.21, 306.58 | 22.6, 20.9 | 1.27 | 49.5, 45.5, 55, 49.5, 50.9, 80, 73.33, 76.67, 78.69, 65.45, 64.23, 66.75, 61.79, 73 |
| Strong              | 225.5, 225.5, 225.5, 225.5, 274.3, 274.3, 274.3, 297.8, 297.8, 157.3, 167.2 | 304.2 | 22.6, 20.9 | 1.26, 2.61, 3.69, 2.27, 2.47, 3.18, 4.49, 2.77, 3, 3.45, 4.87, 3, 3.26 | 20, 30, 30, 30, 21, 21, 21, 21, 21, 21 |

Figure 10: Eightfold cross-validation.
4.2. K-Fold Cross-Validation. To avoid overfitting, the k-fold cross-validation method was used to train and test the model. This method divided the dataset \( D \) into \( k \) mutually exclusive subsets of similar size; that is, \( D = D_1 \cup D_2 \cup \cdots \cup D_k \), \( D_i \cap D_j = \emptyset (i \neq j, i, j = 1, 2, \cdots k) \). Each subset should maintain the consistency of data distribution as much as possible; that is, it is obtained from \( D \) through stratified sampling. The union of the \( (k-1) \) subsets was used as the training set, and the remaining subsets were used as the test set. In this way, \( k \) groups of training sets and test sets were obtained to carry out \( k \) training and testing, and the mean value of the \( k \) test results was returned. The stability and fidelity of the evaluation results of the cross-validation method depend primarily on the value of \( k \).

The advantage of this method is that it does not need to divide the validation set, and the test set is always applied to the final evaluation of the model and can determine an optimal amount of information from the limited data and learn the existing limited data from different angles to avoid local extremum. Figure 10 shows the 8-fold cross-validation (\( k = 8 \)).

4.3. Classifier Performance Measurement Indicator. To evaluate the classification performance of the rockburst proneness evaluation model, some evaluation indicators need to be introduced. Commonly used indicators include precision, recall, and F-score.

The samples were divided into four cases according to their original categories and the learner’s prediction...
categories: true positive (TP: predicted samples are positive, and true samples are positive), false positive (FP: predicted samples are positive, and the true samples are negative), true negative (TN: predicted samples are negative, and true samples are negative), and false negative (FN: predicted samples are negative, and true samples are positive). Let TP, FP, TN, and FN denote the corresponding number of samples, respectively, and TP + FP + TN + FN = the total number of samples. The “confusion matrix” of the classification results is shown in Figure 11.

Precision refers to the proportion of actual positive samples in the samples judged as positive by the evaluation model and is expressed as

\[ \text{Precision} = \frac{TP}{TP + FP}. \]  

Recall refers to the proportion of positive samples correctly determined by the evaluation model in the total positive samples; that is, the number of positive samples classified as positive samples by the classifier. It is expressed as

\[ \text{Recall} = \frac{TP}{TP + FN}. \]

Precision and recall reflect two aspects of classifier performance. Relying solely on a specific indicator cannot comprehensively evaluate the performance of a classifier. In general, the higher the precision, the lower the recall rate; conversely, the higher the recall rate, the lower the precision. To balance the impact of the accuracy and recall rates, a classifier is comprehensively evaluated, and the comprehensive index of the F-score is introduced. The F-score is the harmonic mean of precision and recall and is expressed as

\[ F_\beta = \frac{(1 + \beta^2) \cdot \text{Precision} \times \text{Recall}}{\beta^2 \cdot \text{Precision} + \text{Recall}} \]

\[ = \frac{(1 + \beta^2)}{(1 + \beta^2)} \times \frac{TP}{TP + \frac{FP + FN}{2}} \]

where the value of \( \beta (\beta > 0) \) reflects the relative importance of precision and recall in the performance evaluation and is usually taken as 1.

4.4. Parameter Sensitivity Test for Evaluation Model. The histogram in Figure 12 shows the evaluation results for rockburst proneness under different influencing factors. The average impact of the numerical characteristics method on the accuracy of rockburst proneness evaluation results was 16.26%, and the highest impact was 32.83%. The average impact of weight on the accuracy of rockburst proneness evaluation results was 4.15%, and the highest impact was 12.04%. The average impact of the normalization method on the accuracy of the rockburst proneness evaluation results was 1.7%, and the highest impact was 4.16%. The evaluation accuracy of the method composed of normalization method 2, weight method 2, and numerical characteristics method 3 was the highest (B2-Q2-S3). Therefore, the order of effect of the critical factors affecting the evaluation results of rockburst proneness was numerical characteristics, weight, and normalization methods. The normalization method had little effect on the evaluation results of rockburst proneness and was no longer improved, and only the weight determination method was further improved.

4.5. Improved CRITIC Method. Two problems are encountered while using the CRITIC method. First, owing to the different dimensions and orders of magnitude of each rockburst proneness evaluation index, it is unreasonable to measure the variability of an index by the standard deviation [56]. Second, the correlation between the various rockburst proneness indicators is positive or negative; the same absolute value of positive correlation and negative correlation should reflect the exact correlation between indicators. Therefore, the method is improved in two aspects: (1) the relative standard deviation (RSD) is introduced to replace the standard deviation to measure the variability of the index, and (2) when calculating the quantisation coefficient of the independence degree of each index, \( 1 - r_{kj} \) becomes \( 1 - r_{kj} \). The specific calculation methods are shown in Steps 2, 3, 5, and 6 (Steps 1, 4, and 7 can be seen in Section 2.3.1). Therefore, before using the B2-Q2-S3 method, the weight calculation Q3 method is improved, which is denoted as the MC-IC method.

Step 2. Calculate normalized matrix \( A \) by the Z-score method.

Step 3. Calculate RSD by Equation (19). \( \text{RSD}_j = (s_j/\bar{x}_j) \times 100\% \), \( j = 1, 2, \cdots n \), \( \text{RSD}_j \) represents the RSD of the \( j \)-th indicator.

\[ s_j = \sqrt{\frac{1}{a-1} \sum_{i=1}^{a} (\tilde{a}_{ij} - \bar{a}_j)^2} \]

\[ \bar{a}_j = \frac{1}{a} \sum_{j=1}^{a} a_{ij} \]

where \( \bar{a}_j \) and \( s_j \) are the mean value and standard deviation of the \( j \)-th index, respectively.

Step 5. Calculate the quantitative coefficient of independence of each evaluation index as

\[ \eta_j = \sum_{k=1}^{n} (1 - r_{kj}), \quad j = 1, 2, \cdots, n. \]
Step 6. Calculate the quantisation coefficient of comprehensive information and the degree of independence of each index as

\[ C_j = \text{RSD} / \eta_j = \text{RSD}, \sum_{k=1}^{n} |1 - r_{kj}|, j = 1, 2, \ldots, n. \]  

(21)

5. Results and Validation

5.1. Results. This study used the average accuracy to evaluate the MC-IC rockburst proneness method after 8-fold cross-validation. The confusion matrix including precision, recall, and F1 was used to evaluate the model after validation of the test sets. The 220 group samples were randomly divided into eight groups. Each training set contained 175 group samples, and each test set included 45 sample groups. Six indexes, including \( W_{ct}, \sigma_0 \) (MPa), \( \sigma_c \) (MPa), \( \sigma_\tau \) (MPa), \( B_1 = \sigma_c / \sigma_\tau \), and \( B_2 = \sigma_\sigma_0 / \sigma_c \), were used as inputs, and the rockburst level was used as an output in the MC-IC method. The average accuracy of the 8-fold cross-validation was 93.33%. The test sets’ data included the following number of grade cases: 12 none, 17 light, 10 moderate, and 6 high. The precision, recall, and F1 values are shown in Table 4. The results clearly show that the MC-IC method’s performance in rockburst proneness evaluation was excellent.

5.2. Validation of Model on a New Engineering Project. The Jiangbian Hydropower Station located in Jiulong County,

Table 5: Evaluation results of rockburst proneness in Jiangbian Hydropower Station (**" means misjudgement).

| Sample numbers | \( \sigma_0 \) | \( \sigma_c \) | \( \sigma_\tau \) | \( \sigma_0 / \sigma_c \) | \( \sigma_\tau / \sigma_c \) | \( W_{ct} \) | Actual rockburst level | Rockburst proneness evaluation level |
|----------------|------------|------------|------------|-----------------|-----------------|-----------------|------------------------|------------------------------------|
| 1              | 98.02      | 148.52     | 6.66       | 0.66            | 22.3            | 3.23            | Moderate              | Moderate                           |
| 2              | 116.88     | 162.33     | 12.30      | 0.72            | 13.2            | 5.23            | Strong                | Strong                            |
| 3              | 43.21      | 116.78     | 3.93       | 0.37            | 29.73           | 3.52            | Light                 | Light                             |
| 4              | 45.92      | 109.33     | 3.34       | 0.42            | 32.77           | 2.97            | Light                 | Light                             |
| 5              | 27.60      | 98.56      | 2.31       | 0.28            | 42.73           | 2.17            | None                  | None                              |
| 6              | 76.80      | 156.73     | 7.79       | 0.49            | 20.13           | 3.82            | Moderate              | Moderate                          |
| 7              | 38.12      | 100.32     | 3.49       | 0.38            | 28.77           | 3.02            | Light                 | Light                             |
| 8              | 102.38     | 142.2      | 5.17       | 0.72            | 27.52           | 4.3             | Moderate              | Moderate                          |
| 9              | 110.62     | 160.32     | 9.69       | 0.69            | 16.55           | 5.72            | Strong                | Strong                            |
| 10             | 40.99      | 97.6       | 6.30       | 0.42            | 15.5            | 3.2             | Light                 | Light                             |
| 11             | 58.12      | 100.2      | 3.33       | 0.58            | 30.12           | 4.5             | Light                 | Light                             |
| 12             | 23.39      | 106.32     | 2.92       | 0.22            | 36.42           | 1.75            | None                  | None                              |
| 13             | 81.75      | 125.77     | 12.14      | 0.65            | 10.36           | 5.75            | Moderate              | Moderate                          |
| 14             | 90.99      | 146.75     | 7.58       | 0.62            | 19.35           | 4.5             | Moderate              | Moderate                          |
| 15             | 61.42      | 107.75     | 3.45       | 0.57            | 31.2            | 3.15            | Light                 | Light                             |
| 16             | 104.49     | 160.75     | 13.01      | 0.65            | 12.36           | 5.41            | Strong                | Strong                            |
| 17             | 86.56      | 146.72     | 7.83       | 0.59            | 18.75           | 4.2             | Moderate              | Moderate                          |
| 18             | 118.77     | 162.7      | 5.48       | 0.73            | 29.7            | 3.82            | Moderate              | Strong*                           |
| 19             | 35.34      | 95.5       | 2.26       | 0.37            | 42.3            | 2.75            | None                  | None                              |
| 20             | 39.11      | 105.7      | 2.83       | 0.37            | 37.35           | 3.08            | Light                 | Light                             |

Figure 13: Rockburst in Jiangbian Hydropower Station: (a) moderate rockburst; (b) high rockburst [57].

Table 5: Evaluation results of rockburst proneness in Jiangbian Hydropower Station (**" means misjudgement).
6. Discussion

6.1. Comparison with Other Rockburst Proneness Evaluation Models. The MC-IC rockburst proneness evaluation method was compared with other rockburst proneness evaluation methods, including empirical criteria, cloud-based methods, and both supervised and unsupervised learning methods. The assessment results are presented in Table 6. A total of 175 group samples were used as the training set, and 45 samples were used as the test set. Precision recall, 8-fold cross-validation, and F1 were used to validate the rockburst proneness evaluation model. The empirical criteria included the Russenes criterion \( \frac{\sigma_f}{\sigma_c} \) [25], rock brittleness coefficient criterion \( \frac{\sigma_c}{\sigma_c} \) [19], and elastic energy index \( W_{el} \) [23]. Other cloud-based rockburst proneness evaluation methods included a model combining the grey correlation method, principal component analysis, cloud theory [46], a cloud model with entropy weight [50], a cloud model based on index distance and uncertainty measure [36], and cloud models with attribution weight [47]. The unsupervised learning model included a self-organising map [41], an ant colony clustering algorithm [42], and hierarchical clustering analysis [43]. The supervised learning models included support vector machines [48], artificial neural networks [50], and gradient boosting machines [48].

It can be seen from Table 6 that empirical indicators no longer have advantages in the evaluation of rockburst proneness and cannot flexibly adapt to the irregular fluctuations in the evaluation index values caused by changes in the engineering geological environment. Other cloud-based rockburst proneness evaluation results had the highest accuracy (77.78%) and the lowest accuracy (44.44%). The accuracy of the method established in this study (B2-IQ2-S3) was 93.33%. Three typical unsupervised learning methods and four typical supervised learning methods had the highest accuracy rates in evaluating rockburst propensity, 51.11% and 68.89%, respectively, and their performance was far lower than that of the model established in this study. In summary, the MC-IC rockburst proneness evaluation method showed excellent performance compared to other processes in evaluating rockburst proneness.

6.2. Limitation. Although the MC-IC rockburst proneness evaluation method performed well, further research is still needed. Compared with the large amount of data in machine learning, rockburst data are too few and prone to overfitting, and it is necessary to continuously supplement new rockburst data to improve the databases. In addition, different evaluation methods have different sensitivities to rockburst data, and different methods need to be used to evaluate the data and comprehensively analyse the evaluation results. According to the actual engineering situation, rockburst data and comprehensively analyse the evaluation results.

| Method categories          | Model name                  | Average accuracy | Reference |
|----------------------------|-----------------------------|------------------|-----------|
| Uncertainty theory         | MC-IC method                | 93.33%           | This paper|
| Empirical criteria         | Rock brittleness coefficient criterion \( \frac{\sigma_c}{\sigma_c} \) | 17.78%           | Wang et al. [19] |
| Elastic energy index \( W_{el} \) | GRA-PCA-Cloud              | 44.44%           | Li et al. [46] |
| Other cloud-based method   | EW-Cloud                    | 77.78%           | Zhou et al. [50] |
| Unsupervised learning      | ACC                         | 44.44%           | Gao [42] |
| Supervised learning        | ANN                         | 60.00%           | Zhou et al. [50] |

Ganzi Prefecture, Sichuan Province, is a dam tunnel diversion hydropower station. The diversion tunnel is a deep-buried and ultralong tunnel with a buried depth of more than 300 m accounting for 53% of the total length (9102 m), and the maximum buried depth is 1690 m. The primary lithology of the tunnel rock is biotite granite. The uniaxial compressive strength was approximately 100 MPa, and the strength-stress ratio was 2:4. During construction, many rockbursts of different degrees occurred (Figure 13). A total of 20 rockburst cases at the Jiangbian Hydro-power Station were evaluated using the MC-IC rockburst proneness evaluation method proposed in this study. The results are shown in Table 5, and 19 rockburst cases were correctly evaluated. The accuracy reached 95%, indicating that the MC-IC rockburst proneness evaluation method effectively assessed rockburst proneness and can provide an adequate basis for identifying rockburst hazard areas and establishing deep engineering hazard prevention and control measures.
database is supplemented to establish a more adaptive evaluation model of rockburst proneness.

7. Conclusions

In this study, a cloud model was used to establish a rockburst proneness evaluation model, and the factors affecting the accuracy of the model were studied. The key factors affecting the rockburst proneness evaluation results of the multidimensional cloud model are digital features, weight, and normalization methods. The most convenient digital features were obtained (numerical characteristics 3), and the CRITIC weight determination method was further improved. The following conclusions can be drawn from this study:

1. The elastic deformation energy index $W_{de}$, maximum tangential stress $\sigma_\theta$ (MPa), uniaxial compressive strength $\sigma_\sigma$ (MPa), uniaxial tensile strength $\sigma_\tau$ (MPa), stress brittleness coefficient $B_1 = \sigma_\theta / \sigma_\tau$, and stress coefficient $\rho_\sigma / \rho_\tau$ were selected as the inputs of the rockburst proneness model in the MC-IC evaluation method. The rockburst proneness evaluation levels—none, light, moderate, and high—were used as the method output.

2. A complete rockburst dataset containing the above six indicators were established, and an 8-fold cross-validation and a confusion matrix (precision, recall, and F1) were used to validate the proposed rockburst proneness evaluation method.

3. The MC-IC rockburst proneness evaluation method was used to evaluate the propensity of 20 groups of rockburst cases at riverside hydropower stations. The accuracy rate of 95% was in good agreement with the on-site rockburst situation.

4. The MC-IC rockburst proneness evaluation method was compared with other rockburst proneness evaluation models, including empirical criteria, other cloud-based methods, and both supervised and unsupervised learning methods. It exhibited excellent performance.

Data Availability

All the data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interests.

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Supplementary Materials

Appendix A. Supplementary material. A total of 271 groups of field rockburst data were shown in Table S1. These data can be divided into training sets and test set to build and test the performance of the MC-IC rockburst proneness method. Table S1: rockburst database. (Supplementary Materials)

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