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Application of Cloud Model in Rock Burst Prediction and Performance Comparison with Three Machine Learning Algorithms

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ABSTRACT Rock burst is a common disaster in deep underground rock mass engineering excavation. In this paper, a cloud model (CM) is applied to classify and assess rock bursts. Some main factors that influence rock bursts include the uniaxial compressive strength ($\sigma_{\mathbf{c}}$), the tensile strength ($\sigma_{\mathbf{t}}$), the tangential stress (σ_θ), the rock brittleness coefficient ($\sigma_{\mathbf{c}}/\sigma_{\mathbf{t}}$), the stress coefficient ($\sigma_\theta/\sigma_{\mathbf{c}}$), and the elastic energy index ($W_{\mathbf{et}}$), which are chosen to establish the evaluation index system. The weights of these indicators are obtained by the rough set method based on 246 sets of domestic and foreign rock burst samples. The 246 samples are classified by normalizing the data and establishing an RS-CM. The 10-fold cross validation was used to obtain higher generalization ability of models. The classification results of the RS-CM are compared with those of the Bayes, KNN, and RF methods. The results show that the RS-CM exhibits higher values of accuracy, Kappa, and three within-class classification metrics (recall, precision, and the F-measure) than the Bayes, KNN, and RF methods. Hence, the RS-CM, which is characterized by high discriminatory ability and simplicity, is a reasonable and appropriate approach to rock burst classification and prediction. Finally, the sensitivity of six indexes was investigated to take scientific and reasonable measures to prevent or reduce the occurrence of rock bursts.

INDEX TERMS Cloud model, rough set, normalization, performance comparison, rock burst.

I. INTRODUCTION

Rock bursts are common dynamic, spontaneous, and uncontrolled geological hazards associated with deep rock mass engineering excavation. Due to the stress field redistribution during the excavation of rock in high geostress conditions, rock bursts can have serious consequences, such as bursting, stripping, ejecting and other issues, via the sudden release of energy stored in the hard brittle surrounding rock [1]. Since rock bursts can suddenly and intensely occur, they directly threaten the safety of operating personnel and equipment, affect the construction schedule, and can even destroy an entire project. As the buried depth and stress levels have increased, rock bursts have become more frequent in underground engineering [2]. Additionally, as global mining activities have increased, rock burst problems have become increasingly prominent. Therefore, it is of great significance to predict and control rock burst hazards.

Many domestic and foreign experts have studied the mechanisms of rock burst from different angles and proposed prediction methods for rock burst corresponding to various intensities. Early research focused on the grading classification of rock burst by analysing the influence of a single factor. For example, Russenes [3], Turchaninov *et al.* [4], and Hoek and Brown [5] proposed strength criteria based on analysing the relationship between the surrounding rock stress and the occurrence of rock bursts. Lu and Wang [6] believed that the rock lithology (especially the uniaxial compressive strength and the tensile strength) affects the occurrence of rock bursts, and they proposed relevant criteria based on this theory. Kidybiński [7] and Singh [8] proposed an elastic strain energy criterion based on the transformation of energy.

As research has progressed, researchers have found that rock bursts are affected by many factors and are complex, nonlinear, and dynamic phenomena. As a result, integrated prediction research has focused on rock bursts considering various factors and methods. For example, Wang *et al.* [9] successfully predicted the intensity of rock burst with three factors using a fuzzy mathematics comprehensive evaluation method. Zhou *et al.* [10] combined the rough set (RS) and technique for order preference by similarity to an ideal solution (TOPSIS) methods to establish an RS-TOPSIS model for rock burst prediction and applied the model to practical engineering. Hu *et al.* [11] applied the improved matter-element extension model that was established based on the theory of matter-element extension in practical engineering. Dong *et al.* [12] established the random forest (RF) model for rock burst forecasting and achieved good results. Zhou *et al.* [13] applied the k-nearest neighbour (KNN) algorithm to predict the grades of rock bursts. Gong *et al.* [14] applied Bayes theory to build a Bayesian (Bayes) model of rock burst prediction and applied the model in underground engineering. The above methods of predicting and grading rock bursts are from different perspectives, and they have considerably improved rock burst prediction. However, due to the randomness, ambiguity and uncertainty of rock bursts, the theories and methods discussed above may not be applicable in every case. Thus, rock burst classification remains a major challenge, and it is necessary to explore new and effective theories and methods.

The cloud model (CM) considers the uncertainty of conversion between qualitative concepts and quantitative numerical representations and can fully consider the fuzziness and randomness of evaluation indicators and data [15]. Therefore, many researchers have applied the CM to studies of rock burst intensity and grading prediction. Based on cloud theory, Wang *et al.* [16] established a comprehensive evaluation model based on the Delphi method and a normal cloud and then applied the model to classify the intensity of rock bursts in underground engineering. Hao *et al.* [17] established a CM based on the fuzzy C-means (FCM) algorithm and four indicators to estimate the rock burst intensity for 40 cases; the results showed that the model was reasonable. Zhou *et al.* [18] established an entropy-CM to predict the grades of rock bursts. They then applied the model to actual projects and achieved good results. However, there are still some problems with these models, and they cannot completely predict rock bursts. For example, the three models noted above are all based on limited data, and the selection of indicators is not reasonable. Additionally, the weights of indicators are influenced by artificial factors and data limitations. Therefore, these models cannot be applied to most cases in underground engineering, although they can achieve satisfactory results in some cases. Thus, it is necessary to conduct further research on CM to improve the discriminative accuracy.

In this paper, rock burst is classified using a CM with a rough set [19]. Considering the ambiguity and uncertainty of the evaluation index, six typical representative indexes are selected to establish the evaluation index system, and the objective weights of these indexes are obtained based on a large quantity of data and objective methods (e.g., RS). Then, the RS-CM is established based on objective weights, and its performance is evaluated to provide a new approach for the prediction of rock burst intensity.

II. METHODS

A. INDICATOR ANALYSIS

Many studies have shown that the occurrence of rock bursts and the burst intensity are affected by the lithological conditions, the ground stress field and the elastic strain energy of the rock. For example, based on an analysis of the causes of rock bursts, Board and Fairhurst [20] suggested that rock bursts are dependent on two essential factors: internal sources and external sources. Li [21] stated that the occurrence of rock bursts is related to the lithology of the surrounding rocks and that if the surrounding rocks do not possess the required conditions for a rock burst event, only stable damage can occur. Jia [22] argued that the occurrence of rock bursts is closely related to the physical and mechanical properties of the surrounding rocks, such as the tensile strength and the uniaxial compressive strength. Tang and Hudson [23] believed that hard and brittle rock at high stress levels is more prone to rock burst. Thus, an evaluation index system of rock burst should be established to reflect the main characteristics of rock bursts and the properties of the surrounding rock, and the relevant date should be easily obtainable [10]. The uniaxial compressive strength (σ_c), the tensile strength (σ_t) and the tangential stress (σ_θ) can effectively reflect the lithologic conditions of the surrounding rock in practical engineering. The stress coefficient (σ_θ/σ_c) mainly reflects the strength of the rock material. The rock brittleness coefficient (σ_c/σ_t) considers the influences of joints and the block size of the rock mass. The definition of the elastic strain energy index W_{et} is the energy stored in the rock mass due to external forces and deformation. The larger the value of the energy index is, the more likely it is that a rock burst will occur. Thus, these six factors (σ_c, σ_t, σ_θ, σ_θ/σ_c, σ_c/σ_t and W_{et}) are chosen as the factors that influence rock bursts to establish an evaluation index. Although there may be other indicators, considering the difficulty of data collection, the above six indicators are adopted in this paper to establish the CM and assess the grades of rock bursts.

B. THE NORMAL DISTRIBUTION OF PARAMETERS

All the parameters of rock burst indicators are random variables in the acquisition process, and many random variables completely or approximately obey a normal distribution according to the central limit theorem [24]. The data for each indicator are approximately in accordance with a normal distribution for the same level of rock burst based on analysis

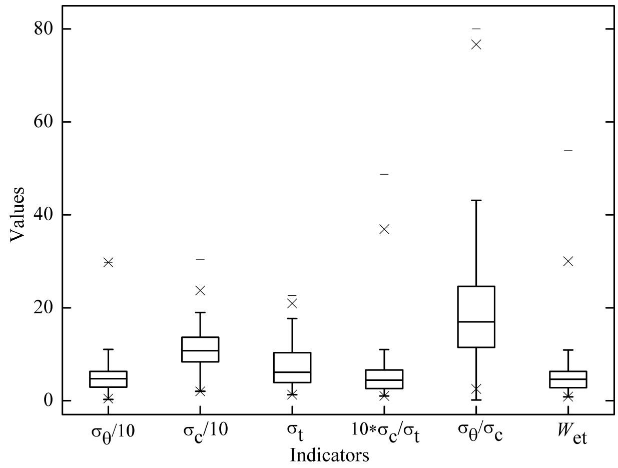

FIGURE 1. Box graph of each parameter.

of the statistical information from various cases, as shown in Table S1 (available in the Supporting Information). The box graph is shown in Fig. 1. The indicators σ_θ and σ_c are divided by 10 and σ_c/σ_t is multiplied by 10 to display all six indicators in one figure. The medians of most of the indicators are not in the centre of the box, which indicates that the distributions of most of the indicators are not symmetric. Moreover, none of the variables have outliers.

The graphs of the probability distributions of σ_θ, σ_c, σ_t, σ_c/σ_t, σ_θ/σ_c and W_{et} in each case are associated with grade II (light rock burst activity) in the database, as shown in Fig. 2. Additionally, this figure shows that all the indicators follow a normal distribution. Therefore, the normal distribution method can be reasonably applied to determine the intensities of rock bursts.

C. THE CLOUD MODEL THEORY

A CM is a type of mathematical model that was first proposed by Li and Du [15] in 1995. It considers the uncertainty of converting between qualitative concepts and quantitative numerical representations. It also fully considers the fuzziness and randomness of the occurrence of rock bursts.

Let Z be a quantitative set, $Z = \{x\}$. C is a qualitative concept in Z, and the definite parameter $x \in Z$ is a random occurrence in C. For any element x of Z, the certainty degree of x in C is $\mu(x) \in [0,1]$, and $\mu(x)$ is a stable random number. The distribution of x in Z is called the cloud, and every x is called a cloud droplet. A cloud that is composed of a large number of cloud droplets can represent a qualitative concept in the domain space.

Three numerical characteristics (E_x, E_n, and H_e) are introduced to express the qualitative concept of cloud theory. Expectation E_x is the expectation of the spatial distribution of cloud droplets in the domain space and the mean value of the set, and E_x is also the point that best represents the qualitative concept. Entropy E_n is determined by the randomness and fuzziness of the qualitative concept. Specifically, E_n is a measure of the randomness and fuzziness of a qualitative concept. Hyper entropy H_e is a measure of the uncertainty of the entropy and reflects the cohesion of the uncertainty at all points in the domain space. The value of hyper entropy H_e indirectly reflects the thickness of cloud droplets [25].

Since the boundary value is the value of the transition from one level to another, the membership in two levels is equal.

$$\exp[-\frac{(C_{\max} - C_{\min})^2}{8E_n^2}] = 0.5 \tag{1}$$

$C_{\max}$ and $C_{\min}$ are the maximum and the minimum thresholds corresponding to the grade standards, respectively. E_n is the entropy of the CM.

The numerical characteristics can be calculated according to Eq. 2.

$$\begin{cases} E_x = (C_{\max} + C_{\min})/2 \\ E_n = (C_{\max} - C_{\min})/2.355 \\ H_e = k \end{cases} \tag{2}$$

In the above expression, $C_{\max}$ and $C_{\min}$ are the maximum and the minimum thresholds corresponding to the grade standards, respectively. k is a fixed value that can be adjusted according to the fuzzy degree of variables and is fixed at 0.01 in this study. The certainty degree of x in C can be calculated by Eq. 3.

$$\mu(x) = \exp(-\frac{(x - E_x)^2}{2 \times (E_n')^2}) \tag{3}$$

where $E_n' \sim N(E_n, H_e^2)$.

CMs can be established by cloud generators. In this paper, forward cloud generators and X-condition cloud generators are used. A forward cloud generator has the ability to convert a qualitative concept to quantitative values, and these generators are used to generate cloud droplets based on the three numerical characteristics of clouds. The forward cloud generator in this study is denoted as CG. An X-condition cloud generator is one type of forward cloud generator that has the ability to generate cloud droplets (x, $\mu(x)$) based on combinations of the three numerical characteristics of clouds and the specified value of x. In this study, this type of generator is denoted as XCG. The processes employed by the two cloud generators are shown in Fig. 3. With the combination of the two generators, various types of clouds can be derived to convert between qualitative knowledge and quantitative values [26].

D. IMPLEMENTATION OF THE APPROACH

Rock bursts are typically divided into four grades [13]: class I (no rock burst activity), class II (light rock burst activity), class III (moderate rock burst activity), and class IV (violent rock burst activity). The process of classifying rock bursts using the CM is as follows.

Step 1: Calculate the three numerical characteristics of the CM for each indicator corresponding to every grade of rock burst intensity according to Eq. (2).

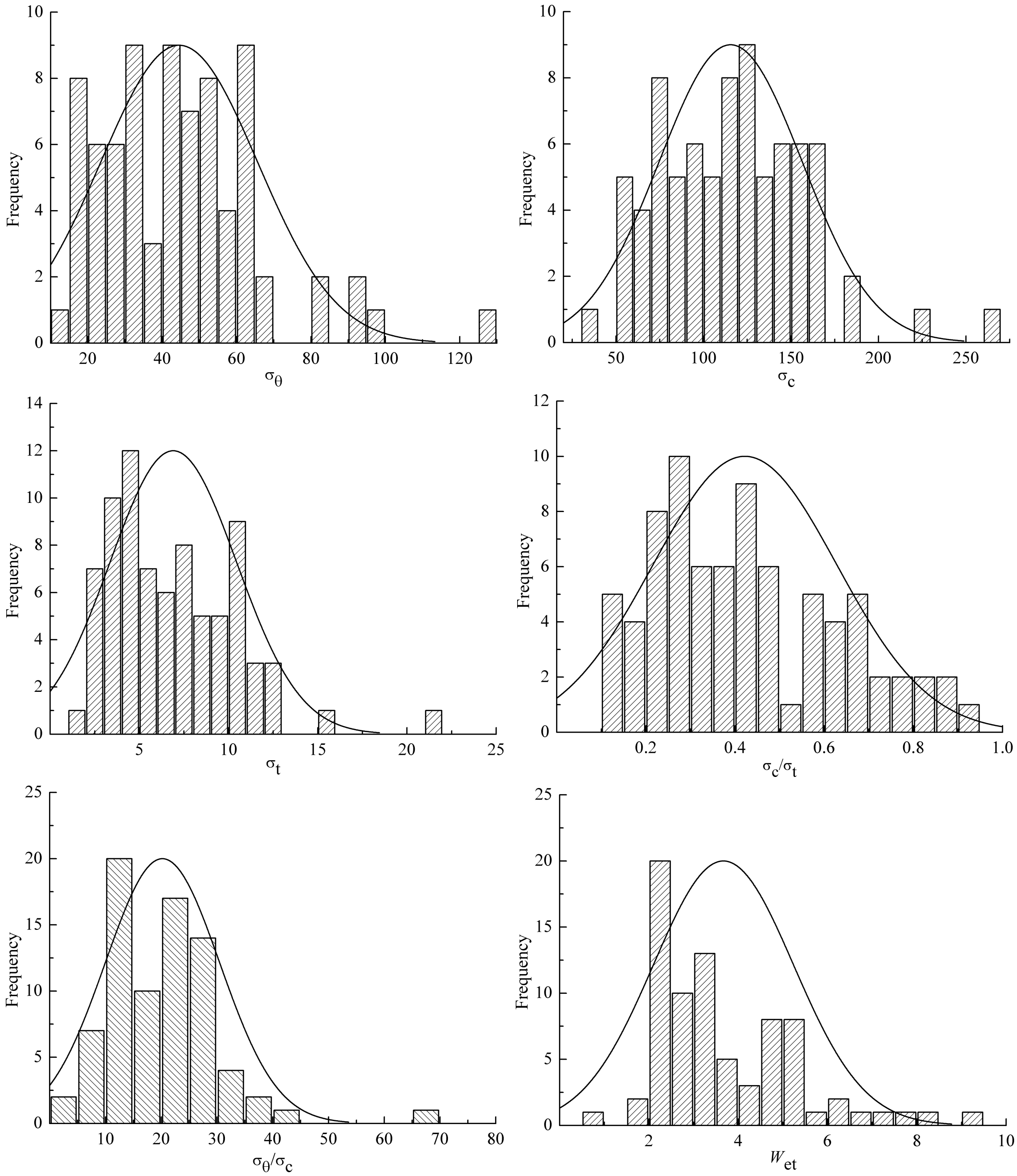

FIGURE 2. Diagrams of the probability distributions of the six indicators.

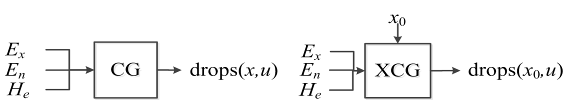

FIGURE 3. Processes used by forward cloud generators and X-condition cloud generators.

Step 2: Establish the CM using the cloud generators, and calculate the certainty degree of each indicator corresponding to each rock burst intensity based on the data collected from underground engineering projects.

Step 3: Calculate the weights of indicators by applying the RS method and the integrated certainty degree as follows.

$$U = \sum_{j=1}^{m} \omega_j \mu(x) \tag{4}$$

where $\mu(x)$ represents the certainty degree of each index and ω_j is the weight of each index.

Step 4: Determine the classes of rock bursts according to the maximum certainty degree principle.

E. ESTABLISHMENT OF THE CLOUD MODEL

There are differences between spatial coordinates and attribute characteristics, such as the associated indicator units and the quantitative degree. The differences may be obvious and influence the prediction of rock bursts. To eliminate the effects, the values of coordinates and attribute characteristics should be preprocessed into dimensionless forms. The data normalization [27] should be performed to eliminate the influence of different units and the quantitative degrees of indicators before the cloud transformation using Eq. (4). If a low indicator value leads to a more favourable indicator effect, the data can be normalized by Eq. (5). Otherwise, if a large indicator value leads to a more favourable indicator, the data can be normalized by Eq. (6).

$$x'_{ij} = \begin{cases} 1, & x_{ij} \leq x_{i\max} \\ 0.25 \times (j - \dfrac{x_{i\max} - x_{ij}}{x_{i\max} - x_{i\min}}), & x_{i\min} < x_{ij} < x_{i\max} \\ 0, & x_{ij} \geq x_{i\max} \end{cases} \tag{5}$$

$$x'_{ij} = \begin{cases} 1, & x_{ij} \geq x_{i\max} \\ 0.25 \times (j - \dfrac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}}), & x_{i\min} < x_{ij} < x_{i\max} \\ 0, & x_{ij} \leq x_{i\min} \end{cases} \tag{6}$$

where j is the grade of the rock burst, x'_{ij} is the normalized value of the indicator, x_{ij} is the original value of this indicator, and $x_{i\max}$ and $x_{i\min}$ are the maximum and minimum values of the indicator, respectively, associated with a ranking grade in Table 1.

TABLE 1. Classification standard for evaluating indicators.

Ranking grade	σ_θ	σ_c	σ_t	σ_c/σ_t	σ_θ/σ_c	W_{et}
I	0-24	0-80	0-5	40.0-55.0	0-0.3	0-2.0
II	24-60	80-120	5.0-7.0	26.7-40.0	0.3-0.5	2.0-4.0
III	60-126	120-180	7.0-9.0	14.5-26.7	0.5-0.7	4.0-6.0
IV	126-200	180-320	9.0-12.0	0-14.5	0.7-1.0	6.0-10.0

After data normalization, the values are transferred into the interval [0, 1]. The four ranking grades (I, II, III, and IV) of the indicators are thus quantitatively expressed by four data intervals of [0.0, 0.25), [0.25, 0.5), [0.5, 0.75), and [0.75, 1.0], respectively.

The numerical characteristic values are calculated according to cloud theory and Eq. 2. Then, the CM can be established using the forward cloud generator. The CM is shown in Fig. 4, where the x-axis is the index value and the y-axis represents the membership of the value.

III. RESULTS AND DISCUSSION

A. WEIGHT CALCULATION AND SENSITIVITY OF INDICATORS

The weights of indicators play a very important role in the process of rock burst assessment. Notably, they can affect the final classification results and final decision making [28]. There are many methods of calculating these weights, and they can be divided into subjective and objective methods. Each type of method has advantages and disadvantages.

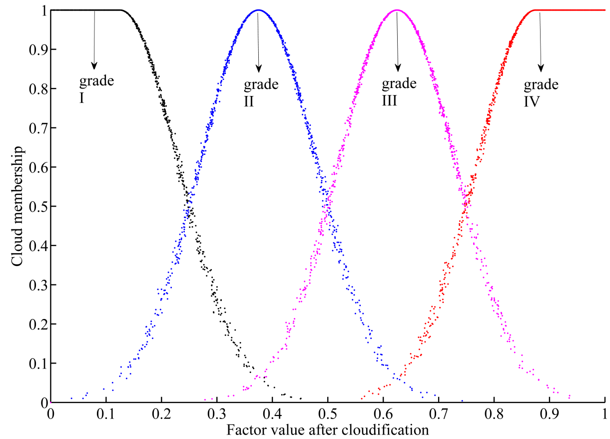

FIGURE 4. The cloud model of indicators after data normalization.

The subjective method is restricted by the subjective consciousness of experts, and the weights are not reliable. The weights of the objective method are objective and reliable because they are calculated based on statistical data [29]. Therefore, the objective weights of the evaluation index are obtained based on the RS method in this paper.

The RS theory [19] is a data-mining method that was proposed by Polish mathematician Zdzislaw Pawlak. This method mines incomplete data and finds hidden information. It has unique advantages in terms of determining the weights of evaluation factors and can remove the influence of artificial factors. The main process [30] used to calculate weights in the RS method is as follows.

Step 1: Discretize the data and build the knowledge base $T = (U, C)$ according to the attributes of indicators. U is the domain, $C = \{c_1, c_2, \ldots, c_n\}$ is a set of conditional attributes, and c_n is the conditional attribute corresponding to a certain factor.

Step 2: Delete the objects with the same attribute values (that is, eliminate duplicate rows of data) to simplify the decision-making table and reduce the calculation time.

Step 3: Calculate the equivalent class partition $U/C = \{X_1, X_2, \ldots X_n\}$ of the conditional attribute set C in the domain U.

Step 4: Calculate $|C| = \sum_{i=1}^{n} |X_i|^2$, where $|X_i|$ is the cardinality of the set (the number of elements).

Step 5: Calculate the partition $U/\{c_i\} = \{Z_1, Z_2, \ldots, Z_n\}$ of each conditional attribute c_i in the domain U and the importance of x as $Sig(x) = 1 - \frac{\sum_{i=1}^{m} |Z_i|^2}{Card(U)^2}$, where $Card(U)$ is the cardinality of the set.

Step 6: For each conditional attribute c_i, calculate the partition $U/(C - \{c_i\}) = \{Y_1, Y_2, \ldots, Y_n\}$ of the conditional attribute set C in the domain U after c_i is removed from C. Then, $|C - \{c_i\}| = \sum_{i=1}^{k} |Y_i|^2$ is calculated.

Step 7: Calculate the importance of c_i and normalize the importance of each attribute. The objective weights are based on the data after normalization.

Based on the RS method, the weights of indicators are calculated for 246 sets of cases. As shown in Fig. 5, the weights of σ_θ, σ_c, σ_t, σ_c/σ_t, σ_θ/σ_c and W_{et} are 0.18, 0.24, 0.21, 0.13, 0.12 and 0.12, respectively. The values of all indicators are similar and relatively large, as shown in Fig. 5. The results illustrate that all indicators are important, and it is not reasonable to estimate the rock burst intensity grades using a sole indicator. Hence, it is necessary to choose six indicators to establish the evaluation index system.

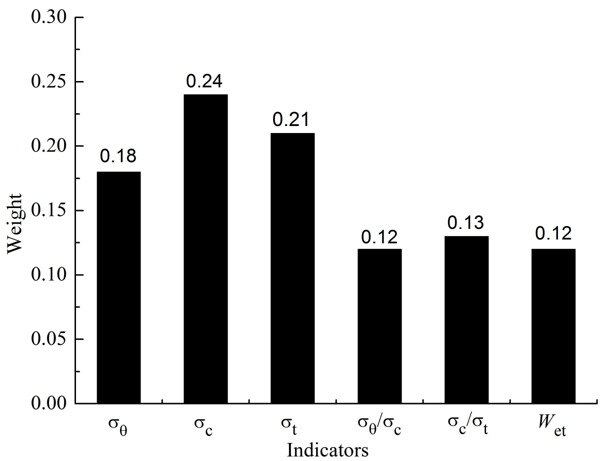

FIGURE 5. The weights of six indicators.

The sensitivity of evaluation indexes should be assessed to determine the importance of indicators and implement measures to prevent rock burst. In this study, σ_c has the largest weight, which suggests that the indicator is more important than all other indicators in contributing to the occurrence of rock burst events. The tensile strength σ_t is the second most important factor with a value of 0.21, and the tangential stress σ_θ is third with a weight of 0.18. Then, σ_c/σ_t, σ_θ/σ_c, and W_{et} are ranked in succession. Thus, σ_c is the most sensitive parameter for rock burst events, followed by $\sigma_{t,}\sigma_\theta$, σ_c/σ_t, σ_θ/σ_c, and W_{et} in succession.

The uniaxial compressive strength σ_c and the uniaxial tensile strength σ_t reflect the mechanical properties of the surrounding rocks. The magnitude of the tangential stress σ_θ is related to the initial stress level and is greatly affected by the shape and size of the cross-section. Through analysing the sensitivity of rock bursts to these indicators, we found that the occurrence of rock burst is closely related to the mechanical properties of the surrounding rocks, and the uniaxial compressive strength and the tensile strength are the major indicators. The initial stress level and the shape and size of the cross-section also play important roles in the occurrence of rock bursts. Therefore, the sensitivity of rock bursts to these indicators can be considered to reduce the extent of and prevent rock burst hazards.

Li *et al.* [21] found that the occurrence of rock bursts is closely related to the properties of the surrounding rocks. If the surrounding rocks do not exhibit the required properties, the occurrence of rock burst will be low, even if the other conditions of rock burst are met. Xu *et al.* [31] believed that lithology is the most important factor that affects the occurrence of rock bursts, especially the uniaxial compressive strength and the tensile strength. The results of this study reflect this theory. Additionally, many researchers have considered the effects of the properties of the surrounding rocks and the external conditions in selecting the indexes of rock burst evaluation, but the sensitivity of rock bursts to these indicators varies. For example, Liu *et al.* [26] adopted σ_θ, σ_c, σ_t, σ_c/σ_t, σ_θ/σ_c and W_{et} indexes to classify the intensity of rock bursts and analysed the indicator sensitivity based on attribute weights. They found that σ_θ/σ_c played the most important role and had the highest attributed weight. Shi *et al.* [32] obtained the weights of the six indexes based on the entropy weight method, and the results showed that the elastic strain energy index W_{et} was the most important factor that influenced the occurrence of rock bursts. Chen *et al.* [33] reported that the uniaxial compressive strength, the tensile strength, the elastic strain energy and the maximum tangential stress were the major factors that influenced the occurrence of rock burst based on analyses of engineering cases. Qin *et al.* [34] calculated the weight of each index using the RS method and found that the uniaxial compressive stress σ_c and stress coefficient σ_θ/σ_c were the most important factors that affected the occurrence of rock bursts. Zhang *et al.* [35] calculated the weights of the indexes with RS theory and found that the brittleness coefficient σ_c/σ_t was a redundant attribute in the process of attribute reduction. Therefore, the uniaxial compressive strength, stress coefficient, elastic strain energy, rock integrity coefficient and stress ratio were adopted in the evaluation index system. The results showed that the stress ratio and elastic strain energy were the most important factors, followed by the uniaxial compressive strength and rock integrity coefficient. Qiu *et al.* [36] obtained the weights of rock burst indexes based on the RS method and found that the stress coefficient and uniaxial compressive strength were the major indicators. The reason for these differences may be that the mechanisms of rock burst are still not fully understood, and the methods of calculating weights are different. One of the objectives of analysing the sensitivity of these indexes in this study is to provide a different perspective for rock burst assessment and prevention.

B. PREDICTION RESULTS OF DIFFERENT MODELS

The tenfold cross validation (10-fold CV) method [37] is commonly used to test the accuracy of algorithms. In this procedure, the data set is randomly divided into 10 subsets. Nine of them are used to develop model, and the remaining subset is used to test the performance of the model. This process is repeated 10 times with different training subsets. At the end, each instance has been used exactly once for testing, and each test will yield a corresponding accuracy.

TABLE 2. Predictive results of classification for four classifiers.

Class label	Samples	Bayes		KNN		RF		CM	
		true	false	true	false	true	false	true	false
I	Training (31)	26	5	23	8	31	0	26	5
	Testing (12)	7	5	8	4	10	2	8	4
II	Training (54)	44	10	36	18	54	0	42	12
	Testing (24)	15	9	11	13	12	12	16	8
III	Training (54)	22	32	34	20	54	0	41	13
	Testing (27)	11	16	13	14	15	12	19	8
IV	Training (31)	20	11	19	12	31	0	25	6
	Testing (13)	8	5	6	7	9	4	11	2

The average of the accuracies is used as an estimate of the precision of the model. The 10-fold CV method is used to optimize the parameters of the model proposed in this study.

Comparing and analyzing the generalization performance of RS-CM for rock burst prediction is the main purpose of this study. According to this, other three supervised learning algorithms, including random forest (RF), Bayesian (Bayes) and k-Nearest Neighbor (KNN), were considered in this study. The four models share certain characteristics that make them interesting to the current analysis: ① they are increasingly used; ② some of them have been used in rock burst prediction tasks with good results; ③ they have efficient implementations; ④ they use different classifiers to reduce the uncertainty of the results that might be related to the algorithm that each classifier use; and ⑤ they are known to enable the analysis of more complex nonlinear relationships.

The RS−CM and KNN, Bayes and RF models are used to predict the intensities of rock burst cases collected from original data. The dataset is randomized into two parts (a training set and testing set) when the cases are classified based on the Bayes, KNN and RF models. A total of 170 cases (approximately 70% of the database) are chosen as the training set, and the remaining 76 cases are considered the testing and used to validate the model performance.

1) RF MODEL

The algorithm has two parameters (one is the number of classification trees n_{tree}, the other is the number of variables m_{try}) that need to be optimized. m_{try} is more sensitive for discriminant accuracy and the discriminant accuracy is affected little by n_{tree}. In this paper, n_{tree} is a constant with a value of 500 according to the research results of Dong [12] and Zhang [38], and then m_{try} is tested for the number of input factors of the rock burst cases. There are six indexes in this study, so the values of m_{try} can be (1, 2, 3, 4, 5, 6). The best choice of m_{try} is 5.

2) BAYES MODEL

The distribution of type is the key parameter for Bayes algorithm, and has two types: normal and kernel. Normal denotes the Gaussian distribution, and kernel represents the density estimation of the kernel density. The results of 10-fold CV shows that a kernel distribution type is the better choice.

3) KNN MODEL

K is a key parameter and represents the number of nearest neighbours considered in the KNN classifier. Based on the 10-fold CV method, K is tuned for 10 values (1, 2, 3, 4, 5, 6, 7, 8, 9) to find the optimal parameter in this study. Finally, $K = 5$ is the best values.

The numbers of training and testing cases for the four rock burst classes are given in Table 2. The values in the "true" columns are the numbers of samples that are truly predicted, and the values in the "false" columns are the numbers of incorrectly predicted samples. The RF method yields satisfactory results for the training set according to the values in Table 2. Although it provides fewer "true" results than the RF model, the CM achieves satisfactory results. For the testing set, the CM correctly determines the most rock burst intensity grades. Hence, the CM has superior discriminant power for rock bursts and is a reasonable method of rock burst classification.

C. MODEL PERFORMANCE EVALUATION

The evaluation of a classifier is just as important as the characteristics of the classifier itself. One of the basic tools for assessing the confidence of classifiers is the confusion matrix. The confusion matrix is an $m \times m$ matrix, as shown in Eq.7. For each model, a confusion matrix is presented [38]. Two global classification metrics (the classification accuracy and Cohen's Kappa index) and three within-class classification metrics (recall, precision, and F-measure) are used to analyse the predictive performance of the four classifiers.

$$\text{matrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mm} \end{bmatrix} \tag{7}$$

where x_{ii} on the main diagonal represents the number of samples of class i that are correctly predicted, x_{ij} represents the number of samples of class i that are wrongly associated with class j, and m is the number of classes.

D. GLOBAL CLASSIFICATION METRICS

The discriminatory ability of the four models can be evaluated according to the discriminant accuracy rate. The accuracy can be calculated by Eq. 8. Cohen's Kappa is the index used to assess the inter-rater reliability when coding categorical variables. The statistic is also considered an improvement over using percentages to evaluate reliability [39]. The Kappa value can be calculated by Eq. 9.

$$\text{Accuracy} = (\frac{1}{n}\sum_{i=1}^{m} x_{ii}) \times 100\% \tag{8}$$

$$\text{Kappa} = \frac{n\sum_{i=1}^{m} x_{ii} - \sum_{i=1}^{m}(x_{i+} \cdot x_{+i})}{n^2 - \sum_{i=1}^{m}(x_{i+} \cdot x_{+i})} \tag{9}$$

where n is the total number of samples in the dataset, x_{i+} is the number of samples of class i, and x_{+i} is the number of samples that are predicted to class j.

The range of Kappa values varies from -1 to 1, and they can be divided into six groups that represent different levels of consistency (as shown in Table 3). In general, if the value of Kappa is less than 0.4, the strength of agreement is poor, and if the value of Kappa is greater than or equal to 0.4, the strength of the agreement is good [40].

TABLE 3. The basic scale of agreement based on the Kappa value.

Strength of agreement	Kappa value
Total disagreement	[-1.0,0.0)
Slight	[0.0,0.2)
Poor	[0.2,0.4)
Moderate	[0.4,0.6)
Substantial	[0.6,0.8)
Perfect agreement	[0.8,1.0)

For the training set and testing set, the accuracy and Kappa results for each model are shown in Table 4. The accuracy of the training set in the four models falls into the range of [0.6588–0.1]. Obviously, the RF model exhibited the highest average accuracy rate (100%), and the CM was second with an average accuracy rate of 76.14%. Both the KNN and Bayes models achieved lower accuracies of 65.88%. The Kappa values of the four models fall into the range of [0.531–1.0]. The Kappa values of the cloud, RF, KNN and Bayes models range from moderate to perfect according to the basic scale shown in Table 3. It is obvious that the Kappa of the RF is the highest at 1.0 and is successively followed by those of the CM, Bayes and KNN models. The results show that the RF model is superior to the other models based on the training samples. For the testing set, the accuracy of the four models varies from 0.50 to 0.7105. The CM has the highest accuracy rate (71.05%) and is successively followed by the Bayes, RF and KNN models, with accuracy rates of 53.95%, 51.32% and 50%, respectively. Moreover, the Kappa values of the cloud, RF, KNN and Bayes models fall into the range of [0.313–0.6]. The agreement strength of Kappa ranges from poor to substantial, and only the Kappa values of the CM and RF model are above 0.4. It is obvious that the Kappa value of the CM is the highest at 0.6 and is successively followed by those of the RF, Bayes and KNN models, as shown in Table 4. Notably, the CM has superior generalization ability for the samples compared to the other models. Thus, the CM is reasonable and can be effectively applied for rock burst classification. Additionally, the accuracy rate and Kappa value are higher for the training set than for the testing set. This result indicates that all four models exhibited superior ability for the training set compared to that for the testing set.

TABLE 4. Global performance metrics of each model.

Classification metrics		Bayes	KNN	RF	CM
Training set	Accuracy	65.88%	65.88%	**100%**	76.14%
	Kappa	0.532	0.531	**1.00**	0.711
Testing set	Accuracy	53.95%	50%	60.53%	**71.05%**
	Kappa	0.363	0.313	0.464	**0.6**

Note: Bolded values indicate the highest values.

E. WITHIN-CLASS CLASSIFICATION METRICS

Three within-class classification metrics, recall, precision and the F-measure, are widely used to evaluate the discriminant power of models. Precision is defined as the ratio of the total number of samples with a certain grade classified correctly to the total number of cases of that grade assessed by a model. Recall is the ratio of the total number of cases with a certain grade classified correctly to the total number of cases of that grade [41]. The two metrics are often combined to provide a single measure called the F-measure. The three metrics are given as follows.

$$\text{Recall}_i = (\frac{x_{ii}}{\sum_{j=1}^{m} x_{+j}}) \times 100\% \tag{10}$$

$$\text{Precision}_i = (\frac{x_{ii}}{\sum_{j=1}^{m} x_{j+}}) \times 100\% \tag{11}$$

$$\text{F-measure} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{12}$$

The results obtained for the three metrics based on the testing set are given in Table 5 for each of the four models. Notably, the recall, precision and F-measure of the four classifiers for rock burst prediction based on the testing set exhibit large deviations (recall = 40.74–84.62%,

TABLE 5. The values of three within-class classification metrics for each model.

Class	Bayes			KNN			RF			CM		
	Recall %	Precision %	F %	Recall %	Precision %	F %	Recall %	Precision %	F %	Recall %	Precision %	F %
I	58.33	58.33	58.33	66.67	47.06	55.17	**83.33**	**76.92**	**80.00**	66.67	66.67	66.67
II	62.50	44.12	51.72	45.83	37.93	41.51	50.00	66.67	57.14	**66.67**	**69.57**	**68.09**
III	40.74	61.11	48.89	48.15	65.00	55.32	55.56	60.00	57.69	**70.37**	**73.08**	**71.70**
IV	61.54	66.67	64.00	46.15	60.00	52.17	69.23	45.00	54.55	**84.62**	**73.33**	**78.57**

Note: F represents the F-Measure, and bolded values indicate the highest value of the three metrics in each row.

precision = 37.93–76.92%, and F-measure = 41.51–80.00%). For class I, the best discriminant performance is exhibited by the RF model, with a recall of 83.33%, a precision of 76.92% and an F-measure of 80.00%. The RF model is followed by the CM (recall, precision, and F-measure of 66.67, 66.67 and 66.67%, respectively), and then the Bayes and KNN methods. The performance of the CM may be lower than that of the RF model for class I for two reasons. First, the evaluation system in this study is not perfect, and many more indicators could be adopted. The other reason is associated with the error between the collected data and the actual data. This error is caused by technical limitations and data rounding. For the other three classes, the best discriminant performance is exhibited by the CM (the three metrics of the CM are all above 65%), and the RF method also displays good performance (the three metrics of the RF model are all above 50%, except for the precision of class IV). Obviously, the CM and RF models have the ability to achieve satisfactory results for every grade, and the CM method is superior to the RF, Bayes and KNN methods.

IV. FURTHER DISCUSSION

The purpose of studying the prediction of the rock burst intensity in this paper is to find scientific and reasonable measures to prevent or reduce the occurrence of rock bursts. The sensitivity of various indicators can provide useful information for rock burst prevention and control. In this study, σ_θ, σ_c and σ_t are the major factors of influence, and σ_c/σ_t, σ_θ/σ_c and W_{et} are secondary factors. The finding in this study is in accordance with that obtained by Liu *et al.* [26]. Zhou *et al.* [13] also introduced the six indexes to predict rock burst, indicating that rock burst is more sensitivity to the factors in his study.

Larger values of σ_θ, σ_c and σ_t lead to a higher probability of rock burst occurrence. Hence, it can be concluded that the occurrence of rock burst hazards can be mitigated by controlling the values of these major factors.

Reductions in the tangential stress σ_θ are the primary measure for rock burst prevention. The concentration of the tangential stress is directly affected by the initial ground stress and the relationship between the axial direction of the section and the direction of the maximum principal stress. Additionally, the initial stress is affected by the cross-sectional shape and size [42]. Therefore, the shapes and sizes of excavation sections should be controlled with a proper design to reduce areas of concentrated stress. In actual engineering, the shape of a cross-section should be designed as an ellipse or horseshoe, and the diameter should be reduced at high ground pressures. Moreover, the direction of the sectional axis should be as parallel as possible to the direction of the maximum principal stress.

Water has a softening effect on the surrounding rock, and water-saturated rocks have lower values of uniaxial compressive strength and tensile strength than do dry rocks [43]. In addition, water pressure can reduce the elastic strain energy of rocks by expanding existing cracks and creating new cracks in rock masses. Hence, pouring water on the surface of the surrounding rock can soften the surrounding rock and reduce the risk of rock bursts in excavation engineering.

Because of the complexity of rock bursts, the associated hazards are far from controlled, and work is continuously needed to identify and implement new control methods. Although rock bursts cannot be completely eliminated completely based on the findings of this study, a new approach is provided for rock burst prediction and prevention.

V. CONCLUSION

Supervised learning algorithms for predicting rock burst can be valuable methods in actual projects. In this study, RF, KNN, Bayes and cloud model are applied to discriminate rock burst. Based on an analysis of the results of the four models, the conclusions can be stated as follows.

(1) Six quantitative indicators (σ_θ, σ_c, σ_t, W_{et}, σ_θ/σ_c, and σ_c/σ_t) are chosen to build an evaluation index system for rock bursts. The weight of each indicator calculated by the RS method is 0.18, 0.24, 0.21, 0.13, 0.12 and 0.12, respectively.

(2) The classification accuracies of the Bayes, KNN, RF and cloud models are 53.95%, 50%, 60.53% and 71.05%, respectively, and the associated Kappa values are 0.363, 0.313, 0.464 and 0.6, respectively. Moreover, for class I, the recall, precision and F-measure values of the CM are higher than those of the Bayes and KNN methods and lower than those of the RF method. For other class labels, the three metrics of the CM are higher than those of the Bayes, KNN and RF models. The CM is feasible method to predict rock burst.

(3) The sensitivity order of those indicators is: $\sigma_c > \sigma_t > \sigma_\theta > \sigma_c/\sigma_t > \sigma_\theta/\sigma_c = W_{et}$. σ_θ, σ_c, and σ_t are the main factors of influence. Reducing concentrated tangential stresses can be considered the primary measure for decreasing or eliminating the occurrence of rock burst hazards.

Rock burst is a very complex nonlinear dynamic phenomenon and is affected by many factors. Therefore, the CM established in this paper should be further optimized to improve the discriminatory accuracy. For example, the evaluation index system requires further improvement, development and practical application.

REFERENCES

[1] S. T. Zhu, Y. Feng, and F. X. Jiang, "Determination of abutment pressure in coal mines with extremely thick alluvium stratum: A typical kind of rockburst mines in China," *Rock Mech. Rock Eng.*, vol. 49, no. 5, pp. 1943–1952, 2016.

[2] W. D. Ortlepp and T. R. Stacey, "Rockburst mechanisms in tunnels and shafts," *Tunneling Underground Space Technol.*, vol. 9, pp. 59–65, Jan. 1994.

[3] B. F. Russenes, "Analysis of rock spalling for tunnels in steep valley sides," M.S. thesis, Dept. Geol., Norwegian Inst. Technol., Trondheim, Norway, 1974. [Online]. Available: https://scholar.google.com/scholar?hl=zh-CN&as_sdt=0%2C5&q=Analysis+of+rock+spalling+for+tunnels+in+steep+valley+sides&btnG=

[4] A. Turchaninov *et al.*, "State of stress in the upper part of the Earth's crust based on direct measurements in mines and on tectonophysical and seismological studies," *Phys. Earth Planet. Interiors*, vol. 6, no. 4, pp. 229–234, 1972.

[5] E. Hoek and E. T. Brown, "Practical estimates of rock mass strength," *Int. J. Rock Mech. Mining Sci.*, vol. 34, pp. 1165–1186, Dec. 1997.

[6] J. Y. Lu and C. M. Wang, "Study on back analysis for stress of rock mass from information of rockbursts," *J. Yangtze River Sci. Res. Inst.*, vol. 11, no. 3, pp. 27–30, 1994.

[7] A. Kidybiński, "Bursting liability indices of coal," *Int. J. Rock Mech. Mining Sci. Geomech. Abstr.*, vol. 18, pp. 295–304, Aug. 1981.

[8] S. P. Singh, "Classification of mine workings according to their rockburst proneness," *Mining Sci. Technol.*, vol. 8, pp. 253–262, May 1988.

[9] Y. H. Wang, W. D. Li, Q. G. Li, Y. Tsui, and L. G. Tham, "Method of fuzzy comprehensive evaluations for rockburst prediction," *Chin. J. Rock Mech. Eng.*, vol. 17, no. 5, pp. 493–501, 1998.

[10] K. P. Zhou, T. Lei, and J. Hu, "RS-TOPSIS model of rockburst prediction in deep metal mines and its application," *Chin. J. Rock Mech. Eng.*, vol. 32, pp. 3706–3710, Jul. 2013.

[11] J. H. Hu, J. L. Shang, and K. P. Zhou, "Improved matter-element extension model and its application to prediction of rockburst intensity," *Chin. J. Nonferrous Met.*, vol. 23, no. 2, pp. 496–501, 2013.

[12] L.-J. Dong, X.-B. Li, and K. Peng, "Prediction of rockburst classification using Random Forest," *Trans. Nonferrous Met. Soc. China*, vol. 23, pp. 472–477, Feb. 2013.

[13] J. Zhou, X. B. Li, and S. M. Hani, "Classification of rockburst in underground projects: Comparison of ten supervised learning methods," *J. Comput. Civil Eng.*, vol. 30, no. 5, pp. 1–19, 2015.

[14] F. Q. Gong, X. B. Li, and W. Zhang, "Rock burst prediction of underground engineering based on Bayes discriminant analysis method," *Rock Soil Mech.*, vol. 31, no. 1, pp. 370–377, 2010.

[15] D. Li and Y. Du, *Artificial Intelligence With Uncertainty*. Berlin, Germany: National National Defense Industry Press, 2005.

[16] Y.-C. Wang, H.-W. Jing, Q. Zhang, L.-Y. Yu, and Z.-M. Xu, "A normal cloud model-based study of grading prediction of rockburst intensity in deep underground engineering," *Rock Soil Mech.*, vol. 36, no. 4, pp. 1190–1193, 2015.

[17] J. Hao, K.-B. Shi, X.-L. Wang, X.-J. Bai, and G.-M. Chen, "Application of cloud model to rating of rockburst based on rough set of FCM algorithm," *Rock Soil Mech.*, vol. 37, no. 3, pp. 859–865, 2016.

[18] K.-P. Zhou, Y. Lin, J.-H. Hu, and Y.-L. Zhou, "Grading prediction of rockburst intensity based on entropy and normal cloud model," *Rock Soil Mech.*, vol. 37, no. S1, pp. 596–602, 2016.

[19] S. Barbagallo, S. Consoli, N. Pappalardo, S. Greco, and S. M. Zimbone, "Discovering reservoir operating rules by a rough set approach," *Water Resour. Manage.*, vol. 20, no. 1, pp. 19–36, 2006.

[20] M. Board and C. Fairhurst, *Rockbursts: Prediction and Control*. London, U.K.: Inst. Mining Metall., 1984.

[21] X. B. Li, *Rock Dynamics Fundamentals and Applications*. Rockville, MD, USA: Science Press, 2014.

[22] Y. P. Jia, "Study on prediction method and theorial model of rockburst," Ph.D. dissertation, Zhejiang Univ., Hangzhou, China, 2014.

[23] C. A. Tang and A. Hudson, *Rock Failure Mechanisms Explained and Illustrated*. Boca Raton, FL, USA: CRC Press, 2010.

[24] P. Ju and Y. H. Zhai, "Lithology identification analysis based on normal distribution theory and fuzzy synthetic evaluation method," (in Chinese), *Sci. Technol. Eng.*, vol. 12, pp. 1671–1815, 2012.

[25] K.-P. Zhou, Y. Lin, H.-W. Deng, J.-L. Li, and C.-J. Liu, "Prediction of rock burst classification using cloud model with entropy weight," *Trans. Nonferrous Met. Soc. China*, vol. 26, pp. 1995–2002, Jul. 2016.

[26] Z. B. Liu, J. Shao, W. Y. Xu, and Y. D. Meng, "Prediction of rock burst classification using the technique of cloud models with attribution weight," *Natural Hazards*, vol. 68, no. 2, pp. 549–568, 2013.

[27] Z. Liu, J. Shao, W. Xu, and F. Xu, "Comprehensive stability evaluation of rock slope using the cloud model-based approach," *Rock Mech. Rock Eng.*, vol. 47, no. 6, pp. 2239–2252, 2014.

[28] C.-G. Guo, Y.-X. Liu, S.-M. Hou, and W. Wang, "Innovative product design based on customer requirement weight calculation model," *Int. J. Automat. Comput.*, vol. 7, no. 4, pp. 578–583, 2010.

[29] X. Fan, G. Zhang, and K. Wang, "Development of new variance reduction methods based on weight window technique in RMC code," *Prog. Nucl. Energy*, vol. 90, pp. 197–203, Jul. 2016.

[30] Q. Yang, P. A. Du, Y. Wang, and B. Liang, "A rough set approach for determining weights of decision makers in group decision making," *PLoS ONE*, vol. 12, pp. 1–12, Feb. 2017.

[31] D. Q. Xu, N. B. Qin, and Y. B. Zhang, "Forecast and mechanism of round chamber rock burst," *China Mining*, vol. 3, p. 39, Mar. 2000.

[32] X. Z. Shi, J. Zhou, L. Dong, H. Y. Hu, H. Y. Wang, and S. R. Chen, "Application of unascertained measurement model to prediction of classification of rockburst intensity," *Chin. J. Rock Mech. Eng.*, vol. 29, no. 1, pp. 2720–2726, 2010.

[33] H. Chen, N. Li, D. Nie, and Y. Shang, "Prediction of rockburst by artificial neural network," *Chin. J. Rock Mech. Eng.*, vol. 22, no. 5, pp. 762–768, 2003.

[34] S. W. Qin, J. P. Chen, Q. Wang, and D. H. Qiu, "Research on rockburst prediction with extenics evaluation based on rough set," in *RaSiM7: Controlling Seismic Hazard and Sustainable Development of Deep Mines*, vol. 2, C. A. Tang, Ed. Princeton, NJ, USA: Rinton Press, Aug. 2009, pp. 937–944.

[35] L. W. Zhang, D. Y. Zhang, S. C. Li, and D. H. Qiu, "Application of RBF neural network to rockburst prediction based on rough set theory," *Rock Soil Mech.*, vol. 33, no. S1, pp. 270–276, 2012.

[36] D. H. Qiu, J. P. Chen, and Q. Wang, "Research on rockburst prediction with fuzzy comprehensive evaluation based on routh set," in *Proc. Int. Young Scholars' Symp. Rock Mech.*, 2008, pp. 831–835.

[37] M. Kuhn and K. Johnson, *Applied Predictive Modeling*. New York, NY, USA: Springer, 2013.

[38] X. Zhang, N. Guan, Z. Jia, X. Qiu, and Z. Luo, "Semi-supervised projective non-negative matrix factorization for cancer classification," *PLoS ONE*, vol. 10, no. 9, p. e0138814, 2015.

[39] N. Wongpakaran, T. Wongpakaran, D. Wedding, and K. L. Gwet, "A comparison of Cohen's Kappa and Gwet's AC1 when calculating inter-rater reliability coefficients: A study conducted with personality disorder samples," *BMC Med. Res. Methodol.*, vol. 61, Apr. 2013, Art. no. 13444.

[40] M. J. Warrens, "Cohen's linearly weighted kappa is a weighted average," *Adv. Data Anal. Classification*, vol. 6, no. 1, pp. 67–79, 2012.

[41] A. M. Zahedi and A. G. Sorkhi, "Improving text classification performance using PCA and recall-precision criteria," *Arabian J. Sci. Eng.*, vol. 38, no. 8, pp. 2095–2102, 2013.

[42] Z. M. Xu, R. Q. Huang, X. C. Luo, R. Li, and J. Y. Sun, "Limitations of static load theory in rockburst research and preliminary analysis on dynamics mechanism of rockburst," *Chin. J. Rock Mech. Eng.*, vol. 22, no. 8, pp. 1255–1262, 2003.

[43] Q. H. Wang *et al.*, "Rockburst hazard and its forcast and treatments in underground engineering," *J. Chongqing Univ.*, vol. 26, no. 7, pp. 116–120, 2003.

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