



## Prediction of rock burst classification using cloud model with entropy weight

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**Abstract:** The method of cloud model with entropy weight was adopted for the prediction of rock burst classification. Some main factors of rock burst including the uniaxial compressive strength ( $\sigma_c$ ), the tensile strength ( $\sigma_t$ ), the tangential stress ( $\sigma_\theta$ ), the rock brittleness coefficient ( $\sigma_c/\sigma_t$ ), the stress coefficient ( $\sigma_\theta/\sigma_c$ ) and the elastic energy index ( $W_{et}$ ) are chosen to establish evaluation index system. The entropy–cloud model and criterion are obtained through 209 sets of rock burst samples from underground rock projects. The sensitivity of indicators is analyzed and 209 sets of rock burst samples are discriminated by this model. The discriminant results of the entropy–cloud model are compared with those of Bayes, KNN and RF methods. The results show that the sensitivity order of those factors from high to low is  $\sigma_\theta/\sigma_c$ ,  $\sigma_\theta$ ,  $W_{et}$ ,  $\sigma_c/\sigma_t$ ,  $\sigma_t$ ,  $\sigma_c$ , and the entropy–cloud model has higher accuracy than Bayes, K-Nearest Neighbor algorithm (KNN) and Random Forest (RF) methods.

**Key words:** rock burst; prediction; cloud model; entropy weight; sensitivity

### 1 Introduction

Rock burst is one common kind of dynamic, spontaneous, uncontrolled geological hazard in deep rock mass engineering excavation. Due to the stress field redistribution in rock engineering with the excavation of surrounding rock under high geostress conditions, rock burst leads to a series of unfavorable influences such as bursting, stripping and ejecting, resulting from the sudden release of the stored elastic strain energy from the hard brittle surrounding rock [1]. Since rock burst occurs suddenly and intensely, the rock particles can be ejected with a velocity of 8–50 m/s [2], which threatens the safety of operating personnel and equipment directly, and affects the construction schedule, even destroys the whole project. With the increase of buried depth and the level of stress, rock burst shows a trend of high frequency in underground engineering [3]. With the increase of global mining activities, the problem of rock burst is increasingly prominent. Therefore, it is of great significance to predict and control the hazard of rock burst.

Many experts have studied the mechanism of rock burst from different angles and proposed the prediction

methods of corresponding intensity of rock burst. Early experts studied the prediction of rock burst mainly from single factor. RUSSENE [4], TURCHANINOV et al [5], HOEK and BROWN [6] and TAO [7] believed that rock strength was closely related to the occurrence of rock burst and surrounding rock stress and put forward the strength criterion. GUO [8] believed that lithology especially the uniaxial compressive strength and the tensile strength affected the occurrence of rock burst and proposed the relevant criteria. KIDYBINSKI [9] and SINGH [10] found that energy was an important factor affecting the occurrence of rock burst and put forward the criterion of elastic strain energy.

Along with the further research, people gradually realized that rock burst affected by many factors is a complex nonlinear dynamic phenomenon. As a result, many research scholars carried out intelligent integrated prediction research of rock burst with various factors by intelligent methods. ZHOU and GU [11] established a rock burst orientation of the fuzzy self-organization neural network model based on the GIS space data analysis technology and fuzzy self-organization neural network. WANG et al [12] carried out a prediction study of the occurrence and the size of intensity of rock burst with three main influence factors using the fuzzy

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mathematics comprehensive evaluation method. GONG and LI [13] developed a distance discriminant analysis model for rock burst prediction and forecasted the occurrence of rock burst and the size of intensity based on the theory of distance discriminant analysis. ZHAO [14] and ZHU et al [15] built support vector machines and classification prediction model, and effectively forecast the rock burst. ZHOU et al [16] established a RS-TOPSIS model for rock burst prediction with some related indicators based on the method of technique for order preference by similarity to ideal solution and the theory of rough set and then applied the model to practical engineering. HU et al [17] applied the improved matter-element extension model which was established by the theory of matter-element extension to practical engineering. SHI et al [18] used the unascertained measure theory to establish the unascertained measure model of intensity of rock burst prediction and the model acquired a good effect of rock burst prediction. DONG et al [19] used the method of random forest (RF) classification to predict rock burst and established the random forest model for rock burst forecast. ZHOU et al [20] applied the k-nearest neighbor (KNN) algorithm to predict rock burst of underground engineering. GONG et al [21] built the Bayes discriminant analysis model for rock burst prediction and then applied the model to the practical engineering and achieved good results. The above theories to predict rock burst are from different angles to forecast the rock burst, leading to certain prediction result. However, the classification of rock burst prediction with the influence of the model and parameters uncertainties is a very complicated nonlinear process and classification of rock burst is still a huge challenge. Therefore, the introduction of a new intelligent method for the research of rock burst and intensity classification prediction is still very necessary.

In this work, the prediction and classification of rock burst are focused on using the cloud model with the entropy weight which is based on the uncertainty artificial intelligence [22]. The entropy-cloud model for rock burst prediction is established using the entropy weight method [23] to determine the weight of every index with the forward and backward cloud utilized to calculate numerical descriptors. Then, the model is applied to practical engineering and receives good results. Thus, the model provides a new approach for rock burst prediction research.

## 2 Methodology of cloud model

### 2.1 Cloud model

Cloud model is a mathematical model proposed by LI et al [24] to deal with the transformation of uncertainty knowledge between qualitative and

quantitative on the basis of random mathematics and fuzzy mathematics.

Definition of cloud: set  $U$  as a quantitative set which is expressed by precise values,  $U=\{x\}$ , called domain.  $C$  is a qualitative concept of  $U$ . For any element  $x$  of  $U$ , there is a stable tendency random number  $\mu(x) \in [0,1]$ , which is called the certainty degree of  $x$  to  $U$ , the distribution of certainty degree on  $U$  is called the cloud [25]. There are three numerical descriptors used to express the transformation of cloud including expectation  $E_x$ , entropy  $E_n$ , hyper entropy  $H_e$ .  $E_x$  represents the mean value of the domain; entropy  $E_n$  represents the range of cloud droplets which may be accepted by qualitative concept in domain space; hyper entropy  $H_e$  is entropy of entropy  $E_n$ , reflecting the degree of dispersion of the cloud droplets [26].

Based on the principles of cloud model and concept of cloud numerical descriptors, the numerical descriptors of cloud model [27] can be calculated according to Eq. (1):

$$\begin{cases} E_x = \frac{1}{N} \sum_{i=1}^N x_i \\ E_n = \sqrt{\frac{\pi}{2}} \cdot \frac{1}{N} \sum_{i=1}^N |x_i - E_x| \\ H_e = k \end{cases} \quad (1)$$

where  $X_i=[x_1, x_2, \dots, x_n]$  serves as the value of an indicator belonging to a certain class of rock burst,  $k$  is a constant. Then, the certainty degree of  $x$  to  $C$  [28] can be calculated by Eq. (2):

$$\mu(x) = \exp[-(x - E_x)^2 / (2 \times E_n'^2)] \quad (2)$$

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

Cloud models are executed by cloud generators. There are generally two kinds of cloud generators: the forward and the backward cloud generators. The forward cloud generator which is the transformation between the qualitative knowledge and the quantitative representation is used to generate the cloud drops through the three given cloud numerical descriptors and denoted with CG. Given the three numerical descriptors of cloud and the specified  $x=x_0$ , the combination to generate the cloud drops drop( $x, \mu(x)$ ) is called the  $X$ -condition cloud, which is denoted by XCG. The backward generator is a transferring process to derive the qualitative concept represented by three descriptors from cloud drops and denoted with  $CG^{-1}$ . The cloud generators are shown in Fig. 1. The combination of the two kinds of generators can be used interchangeably to derive various kinds of clouds to bridge the gap between the qualitative concept and the quantitative knowledge [29].

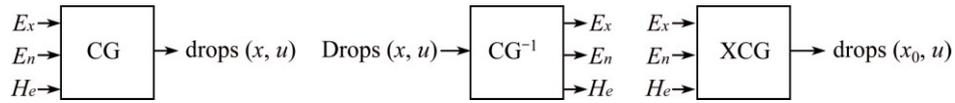


Fig. 1 Process of forward cloud generators, backward cloud generators and X-condition cloud generators

**2.2 Indicator analyses**

The principles of establishing evaluation index system of rock burst are that evaluation indexes should be able to reflect the main characteristics of rock burst and properties of surrounding rock and also should be easy to obtain the data [16]. The uniaxial compressive strength (\$\sigma\_c\$), the tensile strength (\$\sigma\_t\$), the tangential stress (\$\sigma\_\theta\$), the rock brittleness coefficient (\$\sigma\_c/\sigma\_t\$), the stress coefficient (\$\sigma\_\theta/\sigma\_c\$) and the elastic energy index (\$W\_{et}\$) are common indicators and can fully reflect the characteristics of rock burst, thus, the above six indices are chosen as the indicators of rock burst in deep to establish evaluation index system. The uniaxial compressive strength (\$\sigma\_c\$), the tensile strength (\$\sigma\_t\$) and the tangential stress (\$\sigma\_\theta\$) can better reflect lithology conditions of engineering surrounding rock. The occurrence of rock burst and the intensity are affected by lithology conditions and the ground stress field as well as rock elastic strain energy. Therefore, \$\sigma\_c\$, \$\sigma\_t\$, \$\sigma\_\theta\$, \$\sigma\_c/\sigma\_t\$, \$\sigma\_\theta/\sigma\_c\$ and \$W\_{et}\$ are chosen as the evaluation indicators.

**2.3 Entropy weight**

Entropy method is an objective method to calculate the weight of evaluation factors and it acquires the effective and available information by measuring the data [30]. The basic steps of entropy method to calculate weight of each indicator are as follows: 1) structuring matrix \$X=(x\_{ij})\_{m \times n}\$ of the original evaluation data according to the evaluation objects and indicators; 2) normalizing matrix \$X\$; 3) calculating the entropy value \$E\_j\$ and deviation degree \$d\_j\$ of each indicator; 4) calculating the weight of each indicator based on entropy value and deviation degree.

The original data can be normalized by

$$y_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \tag{3}$$

$$y_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \tag{4}$$

where the benefit type indicators are normalized by Eq. (3) and the economical indicators are standardized by Eq. (4).

The entropy value, deviation degree and weight can be calculated by Eqs. (5)–(7), respectively.

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m P_{ij} \ln P_{ij} \tag{5}$$

$$d_j = 1 - E_j \tag{6}$$

$$W_j = d_j / (n - \sum E_j) \tag{7}$$

where \$m\$ is the number of evaluation objects, \$n\$ is the number of evaluation indicators, \$P\_{ij} = y\_{ij} / \sum\_{i=1}^m y\_{ij}\$, if \$P\_{ij} = 0\$, \$\ln P\_{ij} = 0\$.

**2.4 Implementation of approach**

Rock burst is usually divided into four grades [31]: Class I (no rock burst activity), Class II (light rock burst activity), Class III (medium rock burst activity), Class IV (violent rock burst activity). The procedure of the strategy can be processed as follows:

1) Establishing the backward cloud model. Collect data and calculate the numerical descriptors of the cloud model for each index corresponding to each class of rock burst intensity according to Eq.(1).

2) Calculating the weight of each index by entropy method. Firstly, the data are normalized according to Eqs. (3) and (4). Based on Eqs. (5)–(7), the weight of each indicator of evaluation index system of rock burst will be calculated.

3) Establishing the forward cloud model. According to the measured data collected from underground engineering projects combined with Eq.(2), calculate certainty degree of each index corresponding to each rock burst intensity. Then, calculate integrated certainty degree as follows:

$$U = \sum_{j=1}^m \mu(x) \omega_j \tag{8}$$

where \$\mu(x)\$ represents the certainty degree of each index, and \$\omega\_j\$ is the weight of every index.

4) Outputting discrimination result. Discriminate the class of rock burst according to the maximum certainty degree principle, and the class of the maximum certainly degree corresponds to the grade of rock burst intensity. Then, output the grade of rock burst intensity.

**3 Results and discussion**

**3.1 Data collection and analysis**

In order to measure the performance of the model, this study acquired data from 209 cases of rock burst instances collected from the original database built by ZHOU et al [20]. The data are reliable which contain

more than 15 underground engineering projects and 209 rock burst events in the general database obtained from the references published from 1991 to 2013.

The original data set is divided into two sub-sets to implement the entropy-cloud model:

1) Training set (TS). This is required to train the model. 167 out of a total of 209 data sets (approximately 70% of the available data) are considered for training.

2) Testing (prediction) set (PS). This is required to estimate the performance of the model. The reserved 42 data sets are used for predicting.

These rock burst events are of a wide range of engineering types (the hydropower station tunnels, nuclear cooling tunnels, coal mines and metal mines) and locations (China, Norway, Sweden, Italy, etc.). The distribution of the data is shown in Fig. 2(a) as a pie chart illustrating the proportion of the four types of rock burst in underground engineering: none (no rock burst activity, 43 cases), light (light rock burst activity, 56 cases), medium (medium rock burst activity, 66 cases), and violent (violent rock burst activity, 44 cases). The scatter plot matrix of the original data set is given in Fig. 2(b). No obvious correlation among the variables is observed. The box plot of the original data set is given in Fig. 2(c). The indicators  $\sigma_\theta$  and  $\sigma_c$  are separately divided by 10, and  $\sigma_\theta/\sigma_c$  times 10 in Fig. 2(c) in order to well display all the indicators in one figure. For most of the data groups, the median is not in the center of the box, which indicates that the distribution of most of the data groups is not symmetric. In addition, dependent variables of  $W_{et}$ ,  $\sigma_\theta/\sigma_c$ ,  $\sigma_c/\sigma_t$ ,  $\sigma_c$  and  $\sigma_t$  do not have any outlier whereas  $\sigma_\theta$  has outliers. It is obvious that 209 cases collected in this work are reasonable according to Fig. 2.

### 3.2 Numerical descriptors of cloud

The steps of calculating numerical descriptors of cloud using forward cloud and backward cloud theory are as follows. Firstly, the collected data cases are

grouped according to the principle of taking the data with the same class of rock burst into one group. Secondly, calculate the numerical characteristics of cloud model according to analysis of each set of data by Eq. (1). Then, run forward cloud generator to generate cloud droplets. Finally, the final cloud numerical descriptors are obtained through analyzing the cloud droplets with backward cloud models. The results are shown in Table 1.

It can be found from Table 1 that each indicator has large values of mean square deviation. The parameter value ranges intersect each other and do not have very obvious boundaries. This will make it difficult to obviously classify those rock burst events with a satisfactory accuracy. So, the combination of multiple indicators is required to gain a better discriminant result.

### 3.3 Entropy weight and sensitivity of indicators

According to entropy method, entropy value and weight of each indicator are calculated, as shown in Table 2. It can be found that the entropy values of every indicator are close and relatively large. The results show that it is not reliable to classify the rock burst intensity with sole indicator, because all indicators are important. Fortunately, these indicators can work synthetically so as to obtain significantly better results.

Analyzing the sensitivity of evaluation indexes is conducive to analyzing the importance of indicators and taking measures to prevent rock burst by engineers. The entropy weights shown in Table 2 turn out that the indicator  $\sigma_\theta/\sigma_c$  has the largest weight for the rock burst prediction. It shows that the indicator plays a more important role than other factors to account for the occurrence of rock burst events. The tangential stress  $\sigma_\theta$  takes the second place in entropy weights with value of 0.24, which is followed by the elastic strain energy storage index  $W_{et}$  with weight value of 0.18. Then,  $\sigma_c/\sigma_t$ ,  $\sigma_t$ ,  $\sigma_c$  rank in a successive way. So,  $\sigma_\theta/\sigma_c$  is the most

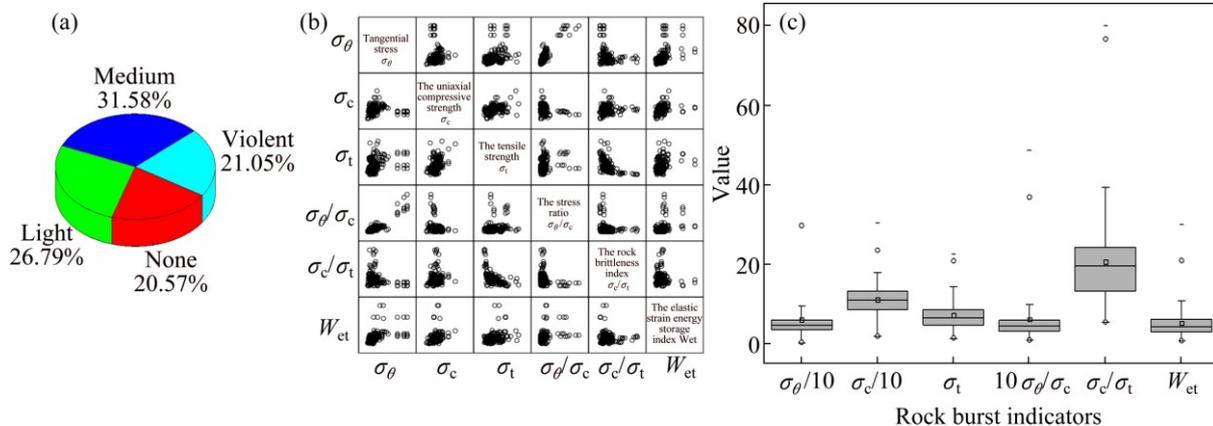


Fig. 2 Data visualization: (a) Pie chart showing distribution of observed rock burst cases; (b) Scatter plot matrix of rock burst cases; (c) Box plot of each variable for rock burst cases

**Table 1** Statistical features of rock burst case data

Activity	Rock burst intensity	Indicator					
		$\sigma_\theta$	$\sigma_c$	$\sigma_t$	$\sigma_\theta/\sigma_c$	$\sigma_c/\sigma_t$	$W_{et}$
No rock burst activity	Mean ( $E_x$ )	22.4	91.2	5.99	0.29	18.4	2.6
	$E_n$	12.6	41.7	3.15	0.2	11.7	1.7
	Mean square deviation	11.82	40.6	3.2	0.21	11.2	1.84
Light rock burst activity	Mean ( $E_x$ )	43.1	115	7	0.38	20.6	3.2
	$E_n$	11	30	2.34	0.14	7.4	0.7
	Mean square deviation	11.98	29.45	3	0.14	9.36	0.76
Medium rock burst activity	Mean ( $E_x$ )	51.4	118	6	0.51	26.6	5.6
	$E_n$	14.8	37.6	3.2	0.12	12.6	1.7
	Mean square deviation	16.75	39.2	3.5	0.14	15.9	2.39
Violent rock burst activity	Mean ( $E_x$ )	132.6	117.6	10.62	1.4	12.6	9.8
	$E_n$	93	46	4.6	1.3	4.2	5.6
	Mean square deviation	89.45	48.8	4.5	1.26	4.7	6.49

**Table 2** Entropy coefficients of evaluation indicators

Coefficient	$\sigma_\theta$	$\sigma_c$	$\sigma_t$	$\sigma_\theta/\sigma_c$	$\sigma_c/\sigma_t$	$W_{et}$
Entropy value	0.9427	0.9877	0.9741	0.9292	0.9732	0.9567
Entropy weight	0.24	0.05	0.11	0.30	0.12	0.18

sensitive parameter for rock burst classification, and the tangential stress  $\sigma_\theta$  is the second most sensitive one and then  $W_{et}$ ,  $\sigma_c/\sigma_t$ ,  $\sigma_t$ ,  $\sigma_c$ , successively. From the perspective of the sensitivity of indicators,  $W_{et}$ ,  $\sigma_\theta/\sigma_c$  and  $\sigma_\theta$  serve as the major factors,  $\sigma_c/\sigma_t$ ,  $\sigma_c$ ,  $\sigma_t$  are secondary factors.

The graphs of rock burst classes with respect to each distinct indicator are shown in Fig. 3. Ideally, in order to be easily and obviously classified, the values of all indicators should only have one class label value. It is apparent that the values of some indicators have more than one corresponding value of the rock burst class label in some events. This is because the indicator values do not have apparent limits among the four classes of rock burst at all. Thus, it is impossible to classify the rock burst cases correctly if merely using one of the indicators. Fortunately, the combination of the six indicators may work well. It is obvious that Figs. 3(a), (d) and (f) are better mannered for classification than Figs. 3(b), (c) and (e), which illustrates that  $\sigma_\theta/\sigma_c$ ,  $\sigma_\theta$  and  $W_{et}$  are more sensitive than  $\sigma_c/\sigma_t$ ,  $\sigma_c$  and  $\sigma_t$ .

### 3.4 Predicted results

The entropy–cloud model (CM) and the models of K-Nearest Neighbor algorithm (KNN), Bayes and Radom Forest (RF) are obtained through training dataset,

and the training and testing datasets are predicted with the models. In estimating the prediction performance of cloud model, the results of rock burst samples collected are discriminated by the entropy–cloud model, and compared with those calculated by the methods of KNN, Bayes and RF [32]. The results and accuracy of each method are shown in Table 3. Where,  $k$  is 5 in KNN method, NTree is 500 in RF method. The accuracy ( $A$ ) is calculated as follows:

$$A=(N_{\text{correct}}/N_{\text{total}})\times 100\% \quad (9)$$

where  $N_{\text{correct}}$  is the number of samples truly predicted and  $N_{\text{total}}$  is the number of total samples.

The numbers of the predicted cases are given for each class of rock burst intensity in Table 3. The numbers in correct columns are the truly predicted samples, and the numbers in missed columns are incorrectly predicted sample numbers. These values give out the performance of the entropy–cloud model and KNN, Bayes and RF methods in the prediction of rock burst classification. It can be concluded according to the numbers in Table 3 that the cloud model with entropy weight can generate satisfactory results for the classification of these cases. The accuracy rate of training set (TS) calculated by the cloud model (82%) is a little higher than those of Bayes (78%) and KNN (60%) in Table 3, but a little lower than that of RF (86%). The accuracy of prediction set (PS) is 76.2% for the cloud model which is higher than those of the methods of Bayes, KNN and RF. That is to say, RF model has superior ability of training samples, while the entropy–cloud model has the superior generalization ability over the samples. Hence, the cloud model with entropy weight is feasible and applicable for the prediction of rock burst classification.

## 4 Conclusions

1) According to the unascertained factors of classification prediction of rock burst, six quantitative indices including  $W_{et}$ ,  $\sigma_\theta/\sigma_c$ ,  $\sigma_\theta$ ,  $\sigma_c/\sigma_t$ ,  $\sigma_c$  and  $\sigma_t$  are chosen to build evaluation index system of rock burst. On the basis of the statistical analysis of data of a large amount of practical engineering, the backward cloud model is used to calculate the three numerical descriptors of each evaluation indicator and the forward cloud model for predicating the rock burst is established.

2) The entropy weights of each indicator and the graphs of rock burst classes with respect to each distinct indicator show that  $W_{et}$ ,  $\sigma_\theta/\sigma_c$  and  $\sigma_\theta$  are the major factors,  $\sigma_c/\sigma_t$ ,  $\sigma_c$  and  $\sigma_t$  are secondary factors. The sensitivity order of those indicators from high to low is successive as  $\sigma_\theta/\sigma_c$ ,  $\sigma_\theta$ ,  $W_{et}$ ,  $\sigma_c/\sigma_t$ ,  $\sigma_t$ ,  $\sigma_c$ , according to the factor priority for rock burst classification.

3) The accuracies of testing samples using the

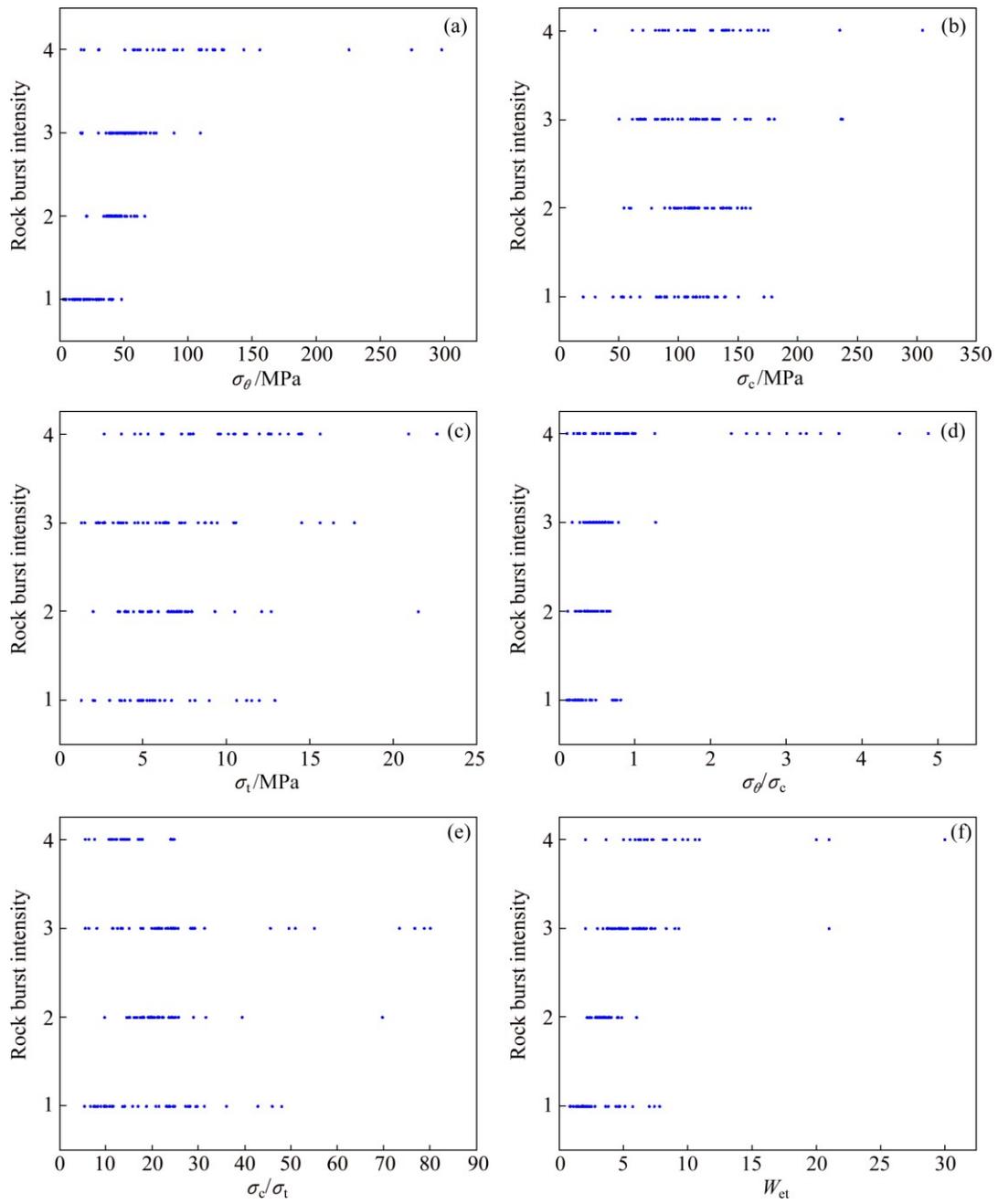


Fig. 3 Rock burst class with respect to each indicator

Table 3 Predictive results of four classification across four models with six indicators

Class label	Data set	Bayes		KNN		RF		CM	
		Correct	Missed	Correct	Missed	Correct	Missed	Correct	Missed
I	TS (33)	26	7	18	15	29	4	27	6
	PS (10)	7	3	5	5	8	2	8	2
II	TS (45)	34	11	27	18	40	5	37	8
	PS (11)	8	3	6	5	9	2	9	2
III	TS (55)	43	12	35	20	47	8	46	9
	PS (11)	7	4	5	6	7	4	7	4
IV	TS (34)	27	7	20	14	28	6	27	7
	PS (10)	6	4	6	4	7	3	8	2
Accuracy/%	TS (167)	78		60		86		82	
	PS (42)	67		52		73.8		76.2	

entropy–cloud model, KNN, Bayes and RF are 76.2%, 52%, 67%, 73.8%, respectively. The accuracies of training samples using the entropy–cloud model, KNN, Bayes and RF are 82%, 78%, 60% and 86%, respectively. The results demonstrate that the entropy–cloud model performs considerably better than KNN, Bayes and RF. The entropy–cloud model has the potential ability for rock burst classification.

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## 熵权-云模型对岩爆等级的预测

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**摘 要:** 采用熵权法和云模型判定岩爆等级。选用岩石的单轴抗压强度  $\sigma_c$ 、单轴抗拉强度  $\sigma_t$ 、切向应力  $\sigma_\theta$ 、岩石的压拉比  $\sigma_c/\sigma_t$ 、岩石的应力系数  $\sigma_\theta/\sigma_c$  和岩石的弹性变形指数  $W_{el}$  作为岩爆等级判定的因素建立岩爆评价指标体系。以收集到 209 组工程中的实际岩爆情况及数据作为样本进行分析计算, 建立岩爆等级判定的熵权-云模型。运用该分析模型分析岩爆评价指标体系中评价指标的敏感性, 并对收集到的工程实例岩爆情况进行判定, 将结果与 Bayes、KNN 和随机森林方法的判定结果进行比较。研究表明: 评价指标体系中指标敏感性由大到小的顺序为:  $\sigma_\theta/\sigma_c$ 、 $\sigma_\theta$ 、 $W_{el}$ 、 $\sigma_c/\sigma_t$ 、 $\sigma_t$ 、 $\sigma_c$ ; 熵权-云模型的判别准确率比 Bayes、K 最邻近结点算法(KNN)和随机森林(RF)方法高。

**关键词:** 岩爆; 预测; 云模型; 熵权; 敏感性

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