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Experimental investigation of predicting rockburst using Bayesian model

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Abstract. Rockbursts, catastrophic events involving the violent release of elastic energy stored in rock features, remain a worldwide challenge for geoengineering. Especially at deep-mining sites, rockbursts can occur in hard, high-stress, brittle rock zones, and the associated risk depends on such factors as mining activity and the stress on surrounding rocks. Rockbursts are often sudden and destructive, but there is still no unified standard for predicting them. Based on previous studies, a new Bayesian multi-index model was introduced to predict and evaluate rockbursts. In this method, the rock strength index, energy release index, and surrounding rock stress are the basic factors. Values from 18 rock samples were obtained, and the potential rockburst risks were evaluated. The rockburst tendencies of the samples were modelled using three existing methods. The results were compared with those obtained by the new Bayesian model, which was observed to predict rockbursts more effectively than the current methods.

Keywords: rockburst; Bayesian model; prediction; risk

1. Introduction

A rockburst is a complex dynamic instability phenomenon (Hedley 1992), which can occur during underground excavation in areas with large in-situ stresses. As a result of the sudden release of accumulated strain energy, rocks can become loose, crack, and even eject violently (Canadian Rockburst Research Program 1996). Rockbursts can damage underground structures and equipments and threaten the health and safety of workers (Sainoki 2016). A tunnel or excavation space may be rendered unusable after an occurrence. As a result, rockbursts are considered a major technical challenge to deep mining efforts. Because they are sudden, disruptive, and complex, accurate prediction of rockbursts is difficult (Blake and Hedley 2003) and remains an urgent problem (Pytlik *et al.* 2016).

The phenomenon has been discussed extensively by many scholars. Rockburst tendency is an important metric to quantify the risk and potential intensity of occurrences and to grade the hazard of an affected mine. However, few methods are still quite accurate prediction, and they are not generally used to predicting rockburst in mines. In recent decades, meaningful advances have been made by many scholars (Singh 1989, Dou *et al.* 2009, Marek 2009, Patynska and Kabiesz 2009, Marian 2011, Shokouhi *et al.* 2017, Li *et al.* 2016). A few have proposed some criteria to better understand the rockburst mechanism, such as strength theory (Hoek and Brown 1980), stiffness theory (Cook 1965) and energy theory (Wiebols and Cook 1968). However, these criteria need to be applied to further field practice. In addition, several indexes have been proposed to measure rockburst tendency, such as burst energy release (Hua and You 2001, Jiang *et al.* 2010), impact energy (Singh 1988) and rock integrity. These criteria derive from the mechanical parameters obtained by testing rock samples. Some important values are compressive strength, tensile strength, capacity to store and release elastic strain energy, and surrounding rock stress and integrity.

In light of the complexity of the rockburst phenomenon, the use of a single parameter is insufficient for prediction purposes. For example, the acoustic emission, chip drilling, removal, vibration, and resistance methods have been proposed and applied, but in isolation, each is lacking in predictive power. As a multifactor, coupling induced dynamic instability, it is essential to establish a calculation method to evaluate the rockburst tendency involving the proper parameters. However, few studies have tried to combine the various factors relating to rockburst hazard. Recently, some interesting models have been derived using artificial intelligence, such as a neural network (Sun *et al.* 2009), fuzzy theory (Adoko *et al.* 2013, Wang *et al.* 2015a) and Bayesian networks (Li *et al.* 2017), along with other integrated analysis methods. These research results indicate that the occurrence of rockbursts is closely related to the mechanical properties of the rock mass, the geological structure, and the surrounding stress. However, these attempts have not yet formed a complete theoretical system. This paper integrates several critical factors into a single model for rockburst tendency prediction.

Bayesian theory, which has been successfully applied in many fields of study, provides a clear and flexible method for making predictions using incomplete knowledge. Heckerman (1990) used a Bayesian framework to improve

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Table 1 Physical data of samples

No.	Height (mm)	Diameter (mm)	σ_c (MPa)	σ_t (MPa)	Modulus (GPa)	Poisson ratio
1	100.72	49.86	100.08	8.46	26.7	0.20
2	100.34	50.27	140.68	10.89	27.1	0.24
3	99.60	50.55	250.54	9.85	31.6	0.19
4	99.82	50.57	88.77	3.74	31.2	0.23
5	100.15	49.98	180.44	8.15	25.8	0.27
6	100.37	49.73	236.80	8.37	22.5	0.23
7	100.34	50.48	120.38	6.53	86.7	0.23
8	99.82	49.79	130.14	6.86	47.5	0.25
9	99.58	49.84	180.13	6.33	51.2	0.26
10	100.84	49.96	64.24	2.14	24.3	0.25
11	100.52	49.96	82.46	4.20	28.7	0.22
12	100.04	50.28	89.33	3.33	29.1	0.20
13	99.15	50.54	120.69	5.41	41.6	0.17
14	99.84	50.58	195.53	7.10	86.2	0.24
15	100.35	49.88	115.50	3.52	29.5	0.23
16	100.37	49.74	150.93	5.42	23.7	0.20
17	100.24	50.58	178.96	4.37	84.8	0.21
18	99.84	49.78	78.84	4.75	37.5	0.27

*σ_c refers to uniaxial compression strength; σ_t refers to uniaxial tensile strength

the process of medical diagnosis. Making full use of its strong information processing ability (Weidl *et al.* 2003), a Bayesian network was applied to the monitoring and management of industrial production processes. A Bayesian model was utilized for choosing investment ventures, and displayed a good ability to cope with future uncertainty (Kemmerer *et al.* 2002). In addition, Bayesian theory was used to identify faults in a computer system (Jensen *et al.* 2001).

Bayesian theory has been demonstrated to be a reliable approach to address complex problems involving many variables with large uncertainties, and models that consider a multi-parameter space are better suited to predicting rockburst tendency than single-variable models. In this study, the main factors affecting risk and intensity of rockbursts were used to make a Bayesian model.

2. Materials and methods

2.1 Materials

In this study, the physical and mechanical parameters of limestone samples were measured. All tested samples were from the Beishan mine in Guangxi province and processed into a standard cylindrical shape 50 mm in diameter and 100 mm in length. The uniaxial compressive strength (σ_c) tests were conducted on a rock mechanics testing system (MTS 815, MTS System Co., Eden Prairie, USA), which is a computer-controlled, servo-hydraulic compression machine. The testing system was a Windows-based platform with visual control operating software, which could record the current time, load, stress, displacement, strain value, load-displacement curve, and stress-strain curve, among other variables. Equal-displacement loading was selected as the control mode for the test. The loading method utilized axial strain control, and the loading rate was 2×10^{-6} mm/mm·s^{-1} until rock failure. The uniaxial tensile strength (σ_t) was obtained by using the Brazilian testing method, and the other parameters were calculated. The results are shown in Table 1.

2.2 Bayesian model

A Bayesian discriminating model is a statistical analysis method commonly used to distinguish between types of samples. The primary procedure is based on an artificial familiarity with known samples and possible attendant consequences. First, the empirical probability and covariance of each classification is analyzed and calculated. Then, a discriminant function is formulated to grade samples. Finally, a posterior probability is calculated to verify the original evaluation. New samples can then be easily classified after being input into model. Here is a detailed derivation following previous author (Gao 1999):

Empirical probability

A sample set can be divided into k categories $G_1,G_2,\ldots G_k$ according to a certain criterion. Assuming each sample has m factors, $x_1,x_2,\ldots x_m$, that are normally distributed, a given sample can be expressed as a m-dimensional array $X_j^{(i)}=[(x_1,x_2,\ldots x_m)_j^{(i)}]^T$, where i=1,2,3,…k, j=1,2,3,…n_i, and $X_j^{(i)}\in G_i$.

If there are a sufficient number of samples, the "empirical probability," which is the probability that a single sample will be classified into G_i, can be expressed as

$$p_i=\frac{n_i}{n_1+n_2+,\ldots,n_k}=\frac{n_i}{\sum_{i=1}^{k}n_i} \tag{1}$$

Mean values and covariance

Moment estimation of mean values and variances can be introduced to generalize the distribution characteristics of the i th category

$$\mu X^{(i)}=\overline{X}^{(i)}=\frac{1}{n_i}\sum_{j=1}^{n_i}X_j^{(i)} \tag{2}$$

$$S_i^2=\frac{1}{n_i-1}\sum_{j=1}^{n_i}(X_j^{(i)}-\overline{X}^{(i)})(X_j^{(i)}-\overline{X}^{(i)})^T \tag{3}$$

$$\sum=\frac{1}{\sum_{i=1}^{k}(n_i-1)}\sum_{i=1}^{k}(n_i-1)S_i^2 \tag{4}$$

where $\overline{X}^{(i)},\mu X^{(i)},S_i^2$ refer to the mean values, expectation of mean values, and covariance of the i th category, respectively. Additionally, Σ stands for the covariance matrix of the overall sample population.

Empirical discriminant

In this Bayesian model, the empirical discriminant of sample classification can be expressed as

$$\omega_i(X)=\mu_i^T\Sigma^{-1}X-\frac{1}{2}\mu_i^T\Sigma^{-1}\mu_i+\ln p_i \tag{5}$$

The discriminating pattern can be simplified to be:

If $\omega_i(X)=\max_{1\le j\le k}\omega_j(X)$, then $X\in G_i$.

Posterior probability and verification

A Bayesian distance discriminant method was used to separate the samples in this paper. The distance of a given sample $X=(x_1,x_2,\ldots x_m)^T$ to the i th category's centroid can be calculated as

$$d_j^2(X)=(X-\mu_j)^T\Sigma^{-1}(X-\mu_j)-2\ln p_j \tag{6}$$

so the posterior probability that X belongs to the i th category can be calculated

$$P(G_j|X)=\frac{\exp[-\frac{1}{2}d_j^2(X)]}{\sum_{i=1}^{k}\exp[-\frac{1}{2}d_i^2(X)]} \tag{7}$$

If $P(G_j|X)>50\%$, then $X\in G_i$.

This confirms the previous result.

3. Key factors of rockburst tendency

3.1 Induced factors

Numerous engineering datasets show that rockbursts have usually occurred in hard-rock zones that were mostly intact and exhibited high strength, while there were few rockbursts in soft-rock areas. Thus, the occurrence of rockbursts is strongly related to the mechanical properties of surrounding rock mass. The development and triggering of a rockburst is a physical process of gradual energy storage and sudden instability, which manifests as a large energy release. Laboratory tests show that these rocks are brittle but high-strength with linear elastic characteristics. The tests also show that these rocks have the characteristics of elastic-brittle failure and the elastic modulus is relative high. As a result, they are prone to brittle failure in the high-stress regime. Excavation can result in stress redistribution and concentration of surrounding rock. Once local brittle failure occurs, the accumulated energy is quickly released, causing a rockburst.

There is a close relationship between the occurrence of a rockburst and the characteristics of the in-situ stress concentration (Zhao *et al.* 2017). Under the same geological conditions, high stress is concentrated in the local rock. Some rock zones have instead low crustal stress levels. An intact rock with high crustal stress usually has a high elastic modulus, which means a large capacity to store strain energy. High stress locations are especially prone to rockbursts, especially zones not in a hydrostatic state. In the stress concentration zones, most rockbursts are attributable to the discordance of three dimensional stresses, which leads to the shear failure of the rock, rapid energy release, and rockburst (Zhang *et al.* 2013).

Deformations within a rock mass are dominated by elastic strain, and most of the brittle rock with high strength belongs to this category. Conversely, a rock mass dominated by plastic deformation can store less energy. In general, high-strength, brittle rock at underground engineering sites is most likely to induce rockburst.

With respect to energy, rock deformation and failure is the result of energy dissipation and release. The relationship between the dissipated energy and released energy was analysed along the uniaxial loading path; therefore, characterizing rockburst tendency using the energy index may be an effective method. The deformation characteristics prior to rock failure can be approximately captured by the stress-strain behaviour (Müller 2007).

Rockburst tendency is used to characterize the risk and intensity of these events. The severity can be estimated using different quantitative or qualitative methods. Generally, rockburst intensity is divided into four levels, namely, strong rockburst, moderate rockburst, weak rockburst, and none.

Most scholars who study rockburst tendency are concerned with the mechanical properties of field rocks, while others believe that the stress state of the surrounding rock mass is more critical. In the previous literature, one or more factors were used to formulate variables to evaluate rockburst tendency. Some factors adopted here are listed in Table 2. We see that rockburst tendency was associated most often with σ_c and σ_θ, and followed by σ_1 and W_{et}.

3.2 Critical factors

There is a complicated, nonlinear relationship between a rockburst and its precipitating factors. In order to make effective prediction of rockbursts, consideration should be given to integrated indexes involving multiple variables. The uniaxial compression strength σ_c and uniaxial tensional

Table 2 Factors associated with rockburst tendency

Scholars	Impact factors					
	σ_1	σ_θ	σ_L	σ_c	σ_t	W_{et}
Russenses (1974)		√		√		
Turchaninov (1981)		√	√	√		
Hoek and Brown (1980)		√		√		
Barton (1974)	√			√	√	
Kidybiński (1981)						√
Tao (1987)	√			√		
Xu (2002)		√		√		
Wang (1998)		√		√		
Zhang (1991)		√		√		√

*σ_1 refers to maximum principal stress, σ_θ refers to maximum tangential stress, σ_L refers to axial stress of surrounding rocks. Additionally, σ_c refers to uniaxial compression strength, σ_t refers to uniaxial tensile strength, W_{et} refers to elastic energy release index of in-situ rocks.

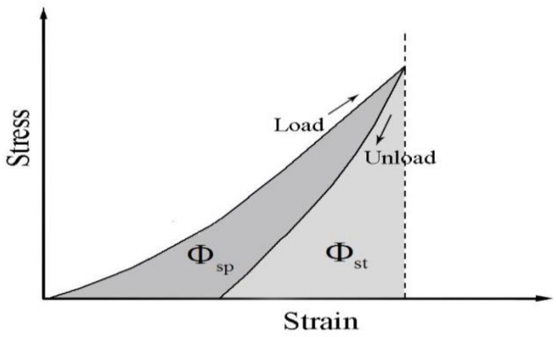

Fig. 1 Energy release index (Kidybiński 1981) during rockburst testing

Table 3 Representative criteria for rockburst tendency

Methods	Formula	Rockburst grades criterion			
		None	Weak	Moderate	Strong
Rock brittleness index (Tan 1991)	$R_b = \dfrac{\sigma_c}{\sigma_t}$	>40.0	26.7. ~40.0	14.5 ~26.7	<14.5
Russense's method (Russense 1974)	$R_\theta = \dfrac{\sigma_\theta}{\sigma_c}$, $\sigma_\theta = \sigma_1 - \sigma_3$	<0.2	0.2 ~0.3	0.3 ~0.55	>0.55
Kidybiński's method (Kidybiński1981)	$W_{et} = \dfrac{\Phi_{sp}}{\Phi_{st'}}$	<2.0	2.0 ~3.5	3.5 ~5.0	>5.0

strength σ_t are the main factors influencing the mechanical properties of rocks. The rock strength-stress ratio R_b, that is, the brittleness coefficient, can be applied to predict rockburst tendency. Generally, larger R_b values are associated with greater risks for rockburst. Hereafter, W_{et} is determined by the uniaxial load/unload curve. In order to obtain the loading/unloading path, the rock is usually loaded to 70%-80% peak stress, and then unloaded to zero. W_{et} equals to the ratio of released energy to the dissipated energy along the loading/unloading path. As shown in Fig. 1, Φ_{sp} is the area between the loading path, and Φ_{st} is the area under unloading path, and the energy index W_{et} is calculated as the area ratio Φ_{sp}/Φ_{st}. This elastic energy release index of rocks has also been used to evaluate rockburst tendency (Kidybiński 1981). Moreover, the axial stress state of the surrounding rock mass was taken into account using Russense's criterion R_θ (Russense 1974), which also greatly influences the risk of rockburst. Physical and mechanical properties, the elastic energy release index, and the stress in the initial rock mass were considered from different perspectives in these methods. A number of single-variable methods have been widely recognized and applied, and three of them are listed in Table 3.

The grading criteria for the different methods are presented on the Table 3. Each row represents a different method, and the columns give the criteria within each for grading rockbusts into the four intensity levels. The three indexes R_b, R_θ and W_{et} were used as the critical factors in this paper.

4. Predicting rockburst risk

Table 4 Critical factors of the training samples

No.	σ_c	σ_t	σ_θ	R_b	R_θ	W_{et}	Actual rockburst grades
1	100.08	8.46	60.70	11.83	0.61	6.56	Strong
2	140.68	10.89	78.40	12.92	0.56	5.52	Strong
3	250.54	9.85	97.55	25.44	0.39	8.60	Strong
4	88.77	3.74	30.53	23.74	0.34	6.23	Moderate
5	180.44	8.15	67.36	22.14	0.37	5.00	Moderate
6	236.80	8.37	109.32	28.29	0.46	4.65	Moderate
7	120.38	6.53	98.68	18.43	0.82	3.50	Moderate
8	130.14	6.86	55.40	18.97	0.43	4.64	Moderate
9	180.13	6.33	65.42	28.46	0.36	3.45	Weak
10	64.24	2.14	18.15	30.02	0.28	4.97	Weak
11	82.46	4.20	21.71	19.63	0.26	2.56	Weak
12	89.33	3.33	27.56	26.83	0.31	3.32	Weak
13	120.69	5.41	30.22	22.31	0.25	4.34	Weak
14	195.53	7.10	42.60	27.54	0.22	5.55	Weak
15	115.50	3.52	11.62	32.81	0.10	2.70	None
16	150.93	5.42	34.21	27.85	0.23	2.80	None
17	178.96	4.37	18.80	40.95	0.11	1.46	None
18	78.84	4.75	13.50	16.60	0.17	3.30	None

* σ_c refers to uniaxial compression strength, σ_t refers to uniaxial tensile strength, σ_θ refers to maximum tangential stress. Additionally, W_{et} refers to elastic energy release index of in-situ rocks.

4.1 Training samples

We have been engaged in field tests and laboratory research on underground engineering dynamic disaster prevention for many years. It was determined that that rockburst grades are approximately normal distribution. That is, strong and very weak rockbursts are relatively less frequent, while moderate and weak rockbursts account for the majority of cases. The Bayesian discriminant model used is based on assuming a normal distribution for the input variables, as well. The geological description, in-situ stress measurement, and laboratory testing procedures were described previously (Wang *et al.* 2015a, b, Wang *et al.* 2016, Wang 2014, Wang *et al.* 2014). Experimental samples were randomly selected from a large data set for training the Bayesian model. The basic parameters of the training samples and associated rockburst grades are listed in Table 4.

4.2 Predicting rockburst tendency using a Bayesian model

In this study, the critical factors $R_b(X_1)$, $R_\theta(X_2)$ and $W_{et}(X_3)$ were used as the basic parameters for predicting rockburst risk in a Bayesian model. The classification categories of rockburst tendency are strong (G_1), moderate (G_2), weak (G_3), and no rockburst (G_4). In other words, all of the basic parameters were included in the three-dimensional matrix $G=(X_1,X_2,X_3)^T$, which forms the dataset of the Bayesian model. These results were calculated as follows:

According to these selected training samples, the empirical probability is

$$p_1 = \frac{3}{18},\ p_2 = \frac{5}{18},\ p_3 = \frac{6}{18},\ p_4 = \frac{4}{18}$$

The mean values of the variable categories are

$$\mu_1(X_1^{(1)}, X_2^{(1)}, X_3^{(1)})^T = (16.73, 0.52, 6.89)$$

$$\mu_2(X_1^{(2)}, X_2^{(2)}, X_3^{(2)})^T = (22.31, 0.48, 4.80)$$

$$\mu_3(X_1^{(3)}, X_2^{(3)}, X_3^{(3)})^T = (25.80, 0.28, 4.03)$$

$$\mu_4(X_1^{(4)}, X_2^{(4)}, X_3^{(4)})^T = (29.55, 0.15, 2.57)$$

The matrix of mean values can be expressed as

$$\overline{X} = \begin{bmatrix} 16.73 & 22.31 & 25.80 & 29.55 \\ 0.52 & 0.48 & 0.28 & 0.15 \\ 6.89 & 4.80 & 4.03 & 2.57 \end{bmatrix}$$

The covariance matrixes of the sample categories were

$$S_1^2 = \begin{bmatrix} 57.16 & -0.85 & 10.86 \\ -0.85 & 0.01 & -0.15 \\ 10.86 & -0.15 & 2.45 \end{bmatrix}$$

$$S_2^2 = \begin{bmatrix} 16.00 & -0.36 & 1.67 \\ -0.36 & 0.04 & -0.16 \\ 1.67 & -0.16 & 0.96 \end{bmatrix}$$

$$S_3^2 = \begin{bmatrix} 15.83 & 0.07 & 2.46 \\ 0.07 & 0.01 & -0.03 \\ 2.46 & -0.03 & 1.26 \end{bmatrix}$$

$$S_4^2 = \begin{bmatrix} 103.77 & -0.36 & -7.36 \\ -0.36 & 0.01 & 0.03 \\ -7.36 & 0.03 & 0.61 \end{bmatrix}$$

The covariance matrix of the sample population was calculated as

$$\Sigma = \begin{bmatrix} 40.63 & -0.27 & 1.33 \\ -0.27 & 0.01 & -0.07 \\ 1.33 & -0.07 & 1.20 \end{bmatrix}$$

While its inverse is

$$\Sigma^{-1} = \begin{bmatrix} 0.03 & 0.56 & 0.01 \\ 0.56 & 113.79 & 6.25 \\ 0.01 & 6.25 & 1.20 \end{bmatrix}$$

The discriminants for sample categories were then obtained:

$$\omega_1(X_1, X_2, X_3) = 0.78x_1 + 111.41x_2 + 11.58x_3 - 77.12$$

$$\omega_2(X_1, X_2, X_3) = 0.92x_1 + 97.77x_2 + 8.88x_3 - 56.56$$

$$\omega_3(X_1, X_2, X_3) = 0.90x_1 + 71.71x_2 + 6.68x_3 - 36.26$$

$$\omega_4(X_1, X_2, X_3) = 0.93x_1 + 49.87x_2 + 4.11x_3 - 24.28$$

Fig. 2 Failure modes of experimental rockbursts

Table 5 Final classifications and posterior probabilities

No.	Discriminants				Classified results	Backward probability
	W_1	W_2	W_3	W_4		
1	75.72	71.84	61.72	43.94	Strong	98.78%
2	59.05	58.80	52.22	38.22	Strong	68.10%
3	85.83	81.22	72.03	54.15	Strong	99.41%
4	51.99	54.18	51.41	40.56	Moderate	80.73%
5	39.76	44.67	43.86	35.48	Moderate	72.29%
6	50.38	55.85	53.40	44.17	Moderate	92.73%
7	69.22	71.60	62.51	48.13	Moderate	86.62%
8	38.94	43.68	42.36	33.67	Moderate	80.92%
9	25.64	35.73	38.46	34.48	Weak	90.47%
10	35.49	42.77	44.24	38.16	Weak	78.26%
11	-2.72	9.95	17.41	17.63	None	65.21%
12	16.77	27.73	32.21	29.70	Weak	88.05%
13	18.56	26.95	30.79	26.80	Weak	94.91%
14	33.05	63.96	41.25	35.01	Weak	94.54%
15	-8.88	7.40	18.55	22.35	None	98.53%
16	2.42	16.05	23.78	24.43	None	74.08%
17	-16.36	4.31	17.91	25.04	None	99.95%
18	-6.79	4.73	13.02	13.26	None	65.71%

5. Results and discussion

The goal of this study is to establish a more reliable model for predicting rockburst risk. Therefore, we introduced a multivariable Bayesian model using real sample data. As shown in Table 5 and Fig. 2, the final classifications and posterior probabilities were calculated, demonstrating a high rate of accuracy. Based on the raw data, the results of predicting rockburst risk using the existing methods were compared. Significant differences were observed between the results of the new method and the previous ones, even for a single sample, as shown in Table 6. With regard to predicting the actual rockburst grades, the accuracy rates of R_b, R_θ and W_{et} in isolation were 61%, 72% and 56%, respectively. However, the multivariable Bayesian model was found to be significantly more reliable, with an accuracy rate of 94%. Only sample No.11 experienced a relatively small error. These results are consistent with the notion that the Bayesian model can achieve more reliable predictions of rockburst risk.

In fact, there are many important factors that influence rockburst tendency. Only a few factors were considered in the previous prediction methods. The rock brittleness index (R_b) only considers the uniaxial compression strength and

Table 6 Comparison of predicted results

No.	Rock brittleness index (R_b)	Russenses's method (R_θ)	Kidybinski's method (W_{et})	Proposed model	Actual rockburst grades
1	***Strong***	***Strong***	***Strong***	***Strong***	***Strong***
2	***Strong***	***Strong***	***Strong***	***Strong***	***Strong***
3	Moderate	Moderate	Strong	Strong	Strong
4	Moderate	Moderate	Strong	Moderate	Moderate
5	Moderate	Moderate	Strong	Moderate	Moderate
6	Weak	Moderate	Moderate	Moderate	Moderate
7	Moderate	Strong	Moderate	Moderate	Moderate
8	***Moderate***	***Moderate***	***Moderate***	***Moderate***	***Moderate***
9	Weak	Moderate	Moderate	Weak	Weak
10	Weak	Weak	Moderate	Weak	Weak
11	Moderate	Weak	Weak	**None**	**Weak**
12	Moderate	Moderate	Weak	Weak	Weak
13	Moderate	Weak	Moderate	Weak	Weak
14	Weak	Weak	Strong	Weak	Weak
15	Weak	None	Weak	None	None
16	***Weak***	***Weak***	***Weak***	***None***	***None***
17	Weak	None	None	None	None
18	Moderate	None	Weak	None	None

* The Bold and Italic words indicate the predicting results are identical using different methods; The Bold words indicate the proposed model don't returned the correct grade.

tensile strength; the stress of surrounding rocks is not included in this model. Russenses's method (R_θ) deals with the principal stress of surrounding rocks and uniaxial compression strength, but it does not account for the accumulated energy and rigidity of the surrounding rock mass. Finally, Kidybinski's method (W_{et}) measures the capacity for rock to store and release elastic energy, while many other factors are ignored. Clearly, there are limitations in the traditional methods for predicting rockbursts. Because rockbursts are induced by multiple factors, considering a single factor alone inevitably leads to imprecise results. Conversely, our model benefitted from integrating the variables used in traditional methods, which could be input into the Bayesian model. In this research, R_b, R_θ and W_{et} were used as the critical factors in proposed model, plus the surrounding rock mass stress σ_1 and σ_θ, and the rock strength σ_c and σ_t.

As shown in Table 6, the results from using the previous methods were inconsistent for all samples, except for #1, 2, 8, and 16. Additionally, at least one method gave the incorrect rockburst grade for all samples besides #1, 2 and 8. On the other hand, the proposed model always returned the correct grade, except for sample 16.

The traditional methods are also limited in that they cannot differentiate the relative importance of the different variables. In addition, it is not always reasonable to update the variables to coordinate the field data. Although certain types of artificial intelligence, such as neural network models, could consider many factors simultaneously, these methods do not address the empirical probabilities and posterior probabilities in their calculations. A Bayesian model, however, can overcome these shortcomings to provide an ideal method for rockburst tendency prediction.

Because of the limited availability of sample data, a self-validation process was implemented on the predictions from the new model. More samples will enable the model to be further optimized and tested, which we plan to perform in future research. However, our results demonstrate that the new model is a significant improvement over existing methods, and can be implemented for reliable rockburst tendency prediction.

The special geological structures would affect the probability of rockburst. When the model is applied in the field, we can get data that most similar to geological conditions according to the geological measurement results, indoor experiments and numerical simulation, this can ensure the accuracy of the results.

6. Conclusions

The occurrence of rockbursts is related to the physical and mechanical properties of rocks and the in-situ stresses of the surrounding environments. Improving upon three traditional prediction methods, we used a Bayesian multi-parameter model to predict rockburst tendency. The predictions of the new model were determined to be more reliable than those from the original methods.

By considering multiple factors, the new model can overcome the limitations of single-factor methods. In this study, all of the parameters and methods were considered in order to eliminate subjective judgments. These variables included the rock brittleness index R_b, Russense's R_θ, Kidybinski's W_{et}, the surrounding rock mass stress σ_L and σ_θ, and the rock strength σ_c and σ_t.

The results demonstrated that the multivariable Bayesian model was highly accurate in predicting rockburst tendency. We recommend that Bayesian models be incorporated in future work on predicting rockburst tendency.

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