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Prediction of rockburst classification using Random Forest

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Abstract: The method of Random Forest (RF) was used to classify whether rockburst will happen and the intensity of rockburst in the underground rock projects. Some main control factors of rockburst, such as the values of in-situ stresses, uniaxial compressive strength and tensile strength of rock, and the elastic energy index of rock, were selected in the analysis. The traditional indicators were summarized and divided into indexes I and II. Random Forest model and criterion were obtained through training 36 sets of rockburst samples which come from underground rock projects in domestic and abroad. Another 10 samples were tested and evaluated with the model. The evaluated results agree well with the practical records. Comparing the results of support vector machine (SVM) method, and artificial neural network (ANN) method with random forest method, the corresponding misjudgment ratios are 10%, 20%, and 0, respectively. The misjudgment ratio using index I is smaller than that using index II. It is suggested that using the index I and RF model can accurately classify rockburst grade.

Key words: mining engineering; tunnel engineering; underground caverns; rockburst; Random Forest

1 Introduction

The increasingly rock engineering projects, such as tunnels, underground cavern, and mining stopes, are constructed at great depth or high tectonics stress fields. The occurrence of rockburst is often during the excavation [1,2]. Rockburst is considered a dynamic instability phenomenon of surrounding rock mass of underground space in high geostatic stress and caused by the violent release of strain energy stored in rock mass. Rockburst occurs during excavating underground space in the form of stripe of rock slices or rock fall or throwing of rock fragments, sometimes accompanied by crack sound. Rockbursts are related to the fracture of rock in place and require two conditions for their occurrence: a stress in the rock mass sufficiently high to exceed its strength, and physical characteristics of the rock which enable it to store energy up to the threshold value for sudden rupture. Rocks which yield gradually in plastic strain under load usually do not generate rockbursts. The likelihood of rock bursts occurring increases as the depth of the mine increases. Rockbursts are also affected by the size of excavation (the larger the more risky), becoming more likely if the excavation size is around 180 m and above. Induced seismicity such as faulty methods of mining can trigger rockbursts. Other causes of rockbursts are the presence of faults, dykes, or joints.

Because it occurs suddenly and intensely, rockburst usually causes injury including death to workers, damage to equipment, and even substantial disruption and economic loss of underground space excavation.

At present, the studies on rockburst have been converted from report on the phenomenon, scale, regularity and hazard of rockburst to the mechanism, the cause of formation, the critical conditions and preventive methods of rockburst. Many scholars have suggested various theories, many prediction methods, and empirical correlation, such as fuzzy comprehensive evaluation [3], analytical principle and problems [4,5], distance discriminant analysis [6], support vector machine (SVM) [7], laboratory integrated evaluation method [8,9], artificial neural network (ANN), prior knowledge and the instability of rock masses [10−16], effects of sonic speed on rockburst location [17], seismological parameters [18], rockburst mechanisms [19], numerical simulation [20,21], case study [22−24], and source location methods [25−29].

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Furthermore, due to the complexity of rockburst mechanism and prediction, study on the mechanism of rockburst, learning of knowledge from rockburst case history and recognition of prevention measurement of rockbursts are comprehensively needed.

Random Forest (RF) and SVM are considered the most effective and reliable new artificial intelligence methods [30−32] for solving classification problems. In this work, according to the practice of complicated problems of the rockburst prediction, the Random Forest is applied to predicting rockburst classification.

2 Criteria and indexes of rockburst

2.1 Criteria considering stress in surrounding rock

The criteria listed in Table 1 were proposed early, and only considered the stress level in surrounding rock. Furthermore, different scholars chose different parameters as evaluation index of criterion for rockburst, and the classification of rockburst intensity also differed from each other. So it is difficult to use these criteria in construction of underground engineering.

2.2 Comprehension criteria considering stress, properties of surrounding rock and energy

1) The following criterion [2] is presented with rockburst tendency index and energy condition of surrounding rock.

$$W_{qx} \geq 1.5 \tag{1}$$

$$\sigma_1 \geq \sigma_c \Big/ \sqrt{\alpha W_{qx}} \tag{2}$$

$$\alpha = 1 + \zeta^2 - 2\mu\zeta \tag{3}$$

$$\zeta = \sigma_2 / \sigma_1 \tag{4}$$

where W_{qx} is the rockburst tendency index; σ_1 and σ_2 are the major and middle principal stress in surrounding rock, respectively; μ is the Poisson ratio.

2) It is stipulated by ZHANG that rockburst could occur if $\sigma_\theta/\sigma_c \leq K_s$, in which the value of K_s related to σ_t/σ_c [3] criterion.

3) KIDYBINSKI [24] proposed an elastic energy index W_{et}. No rockburst activity, medium rockburst activity and violent rockburst activity meet the conditions $W_{et}<2.0$, $2.0 \leq W_{et} \leq 5.0$, and $W_{et}>5.0$, respectively.

2.3 Indexes as input variables for RF

The indexes of criterion should reflect the main factors of rockburst — the properties and stress of surrounding rock. At the same time, they should be obtained easily and can be compared with each other for different cases. In this work, the compressive rock strength σ_c, tensile strength σ_t, elastic energy index W_{et} and the maximum tangential stress σ_θ are chosen as the indexes of criterion. Compressive rock strength σ_c, tensile strength σ_t, and elastic energy index W_{et} can reflect the properties of surrounding rock, and the tangential stress σ_θ can reflect the virgin geostatic stress condition and the influence of the shape and dimension of the underground space on rockburst.

Table 1 Criteria only considering stress in surrounding rock

Scholar	Criteria of rock burst	Source of data
RUSENSES	$\sigma_\theta/\sigma_c<0.20$ (No rockburst activity) $0.20\leq\sigma_\theta/\sigma_c<0.30$ (Light rockburst activity) $0.30\leq\sigma_\theta/\sigma_c<0.55$ (Medium rockburst activity) $\sigma_\theta/\sigma_c\geq0.55$ (Violent rockburst activity)	[2]
HOU et al	$\sigma_1/\sigma_c<0.30$ (No rockburst activity) $0.30\leq\sigma_1/\sigma_c<0.37$ (Light rockburst activity) $0.37\leq\sigma_1/\sigma_c\leq0.62$ (Medium rockburst activity) $\sigma_1/\sigma_c>0.62$ (Violent rockburst activity)	[2]
WANG et al	$\sigma_\theta/\sigma_c<0.30$ (No rockburst activity) $0.30\leq\sigma_\theta/\sigma_c<0.50$ (Light rockburst activity) $0.50\leq\sigma_\theta/\sigma_c\leq0.70$ (Medium rockburst activity) $\sigma_\theta/\sigma_c>0.70$ (Violent rockburst activity)	[3]
HOEK	$\sigma_\theta/\sigma_c = 0.34$ (Light stripping) $\sigma_\theta/\sigma_c= 0.42$ (Violent stripping) $\sigma_\theta/\sigma_c=0.56$ (More lining) $\sigma_\theta/\sigma_c = 0.70$ (Violent rockburst)	[3]
TAO	$\sigma_c/\sigma_1>14.5$ (No rockburst activity) $5.5<\sigma_c/\sigma_1\leq14.5$ (Light rockburst, with light sound) $2.5\leq\sigma_c/\sigma_1<5.5$ (Medium rockburst, with crack sound) $\sigma_c/\sigma_1<2.5$ (Violent rockburst, with strong crack sound)	[4]
TURCHANINOV	$(\sigma_\theta+\sigma_L)/\sigma_c\leq0.3$ (No rockburst activity) $0.3<(\sigma_\theta+\sigma_L)/\sigma_c\leq0.5$ (Rockburst probably) $0.5<(\sigma_\theta+\sigma_L)/\sigma_c\leq0.8$ (Rockburst surely) $(\sigma_\theta+\sigma_L)/\sigma_c>0.8$ (Violent rockburst activity)	[4]
BARTON	$\sigma_c/\sigma_1 = 5-2.5$ and $\sigma_c/\sigma_1= 0.33-0.16$ (Medium rockburst) $\sigma_c/\sigma_1<2.5$ and $\sigma_c/\sigma_1<0.16$ (Violent rockburst)	[5]

In this work, indexes I and II of traditional variables for classifying rockburst are summarized as input variables. Index I of traditional variables includes the maximum tangential stress in surrounding rock mass σ_θ, ratio of tangential stress of surrounding rock and uniaxial compressive σ_θ/σ_c, ratio of compressive rock strength and tensile strength σ_c/σ_t, and elastic energy index W_{et}. Index II of traditional variables includes the maximum tangential stress in surrounding rock mass σ_θ, the compressive strength σ_c, tensile strength σ_t, and elastic energy index W_{et}. Both of two indexes were used to predicting the degrees of rockburst activity using RF.

3 Applications

46 sets of rockburst samples which come from underground rock projects in domestic and abroad were collected to test the rationality of the model (Table 2).

The relationship among the indexes of criteria, the occurrence of rockburst and its intensity is very complex. For the sake of the capability of RF for pattern recognition, we attempt to predict the rockburst activity by using RF. A RF model is established with 350 NTtrees and 2 varibles in rodes.

Four degrees of rockburst activity, including voilent rockburst activity, medium rockburst activity, light rockburst activity, and no rockburst activity, are indicated by 4, 3, 2, and 1, respectively. They are considered output variables in the RF model.

RF model and criterion were obtained through training 36 sets of rockburst samples which come from underground rock projects in domestic and abroad. Another 10 samples were tested and evaluated with the model. The evaluated results agree well with the measured record (MR).

The results of RF method were compared with that of SVM and ANN methods. A SVM model with RBF of kernel function type was established. A neural network was established with three layers. The input layer has 4 neurodes, the hidden layer has 9 hidden neurodes, and the output layer has 2 neurodes. Indexes I and II as input variables, 4 degrees of rockburst activity were considered in the neural network model, which are (0, 0, 0, 1) for voilent rockburst activity, (0, 0, 1, 0) for medium rockburst activity, (0, 1, 0, 0) for light rockburst activity, and (1, 0, 0, 0) for no rockburst activity.

The calculated results of RF, SVM, and ANN are listed in Table 3. It shows that the index I is more reasonable than index II. Misjudgment ratios of tested

Table 2 Collected samples of rockburst cases

No.	σ_θ/MPa	σ_c/MPa	σ_t/MPa	W_{et}	MR	Source	No.	σ_θ/MPa	σ_c/MPa	σ_t/MPa	W_{et}	MR	Source
1	89.56	190.3	17.13	3.97	3	[14]	24	91.3	225.6	17.2	7.3	4	[8]
2	89.56	170.28	12.07	5.76	3	[14]	25	61	171.5	22.6	7.5	2	[8]
3	89.56	187.17	19.17	7.27	3	[14]	26	34.15	54.2	12.1	3.17	2	[9]
4	56.1	131.99	9.44	7.44	3	[13]	27	108.4	138.4	7.7	1.9	4	[9]
5	54.2	133.99	9.09	7.08	3	[13]	28	69.8	198	22.4	4.68	2	[9]
6	70.3	128.52	8.73	6.43	3	[13]	29	105	171.3	22.6	7.27	4	[9]
7	48.75	180	8.3	5	3	[2,6]	30	105	237.16	17.66	6.38	4	[9]
8	62.5	175	7.25	5	3	[2,6]	31	105	304.21	20.9	10.57	4	[9]
9	75	180	8.3	5	3	[2,6]	32	25.49	54.2	2.49	3.17	2	[10]
10	57	180	8.3	5	3	[2,6]	33	72.07	147.09	10.98	6.53	3	[10]
11	89	236	8.3	5	3	[2,6]	34	21.8	160	5.2	2.22	1	[11]
12	50	130	6	5	3	[2,6]	35	20.9	160	5.2	2.22	1	[11]
13	108	140	8	5.5	4	[2,6]	36	12.1	160	5.2	2.22	1	[11]
14	18.8	178	5.7	7.4	1	[2,6]	37*	75	170	11.3	9	3	[2]
15	11	115	5	5.7	1	[2,6]	38*	43.4	123	6	5	3	[2]
16	55.4	176	7.3	9.3	3	[2,6]	39*	62.6	165	9.4	9	3	[2]
17	48	120	1.5	5.8	3	[7]	40*	30	88.7	3.7	6.6	3	[2]
18	63	115	1.5	5.7	3	[7]	41*	105	128.61	13	5.76	4	[9]
19	49.5	110	1.5	5.7	3	[7]	42*	105	304	9.12	5.76	3	[9]
20	30.9	82.56	6.5	3.2	2	[8]	43*	105	306.58	13.9	6.38	4	[9]
21	89	128.6	13.2	4.9	4	[8]	44*	7.5	52	3.7	1.3	1	[12]
22	12.3	237.1	17.66	6.9	1	[8]	45*	24.93	99.7	4.8	3.8	1	[12]
23	55.6	256.5	18.9	9.1	3	[8]	46*	14.96	99.7	4.8	3.8	1	[12]

Cases with * are testing samples

samples using RF, SVM, and ANN are 0, 10%, and 20%, respectively. Misjudgment ratios of training samples using RF, SVM, and ANN are 0, 5%, and 5%, respectively. The calculated probabilities of 4 grades using RF model with index I of training samples are shown in Fig. 1. The calculated probabilities of 4 grades using RF model with indexes I and II for testing samples are shown in Figs. 2 and 3, respectively. It also shows that the index I is more clearly classified than index II. The predicted results of both training and tested samples show that it is feasible and appropriate to use RF model for rockburst prediction with index I.

Table 3 Comparison of calculation results by different methods

No.	MR	RF		SVM		ANN		No.	MR	RF		SVM		ANN	
		I	II	I	II	I	II			I	II	I	II	I	II
1	3	3	3	3	3	3	3	24	4	4	4	4	3	4	4
2	3	3	3	3	3	4	4	25	2	2	2	3	3	2	3
3	3	3	3	4	3	4	4	26	2	2	2	2	2	2	2
4	3	3	3	3	3	3	3	27	4	4	4	4	4	4	4
5	3	3	3	3	3	3	3	28	2	2	2	3	3	2	3
6	3	3	3	3	3	3	3	29	4	4	4	4	4	4	4
7	3	3	3	3	3	3	3	30	4	4	4	4	4	4	4
8	3	3	3	3	3	3	3	31	4	4	4	4	4	4	4
9	3	3	3	3	3	3	3	32	2	2	2	2	2	2	2
10	3	3	3	3	3	3	3	33	3	3	3	3	3	3	3
11	3	3	3	3	3	3	3	34	1	1	1	1	1	1	1
12	3	3	3	3	3	3	3	35	1	1	1	1	1	1	1
13	4	4	4	4	4	4	4	36	1	1	1	1	1	1	1
14	1	1	1	1	1	1	1	37*	3	3	3	3	3	3	3
15	1	1	1	1	1	1	1	38*	3	3	3	3	3	3	3
16	3	3	3	3	3	3	3	39*	3	3	3	3	3	3	3
17	3	3	3	3	3	3	3	40*	3	3	3	3	3	3	2
18	3	3	3	3	3	3	3	41*	4	4	4	4	4	4	4
19	3	3	3	3	3	3	3	42*	3	3	4	3	3	3	3
20	2	2	2	2	2	2	2	43*	4	4	4	4	3	3	3
21	4	4	4	3	4	4	4	44*	1	1	1	2	1	1	1
22	1	1	1	1	1	1	1	45*	1	1	2	1	1	2	2
23	3	3	3	3	3	3	3	46*	1	1	1	1	1	1	1

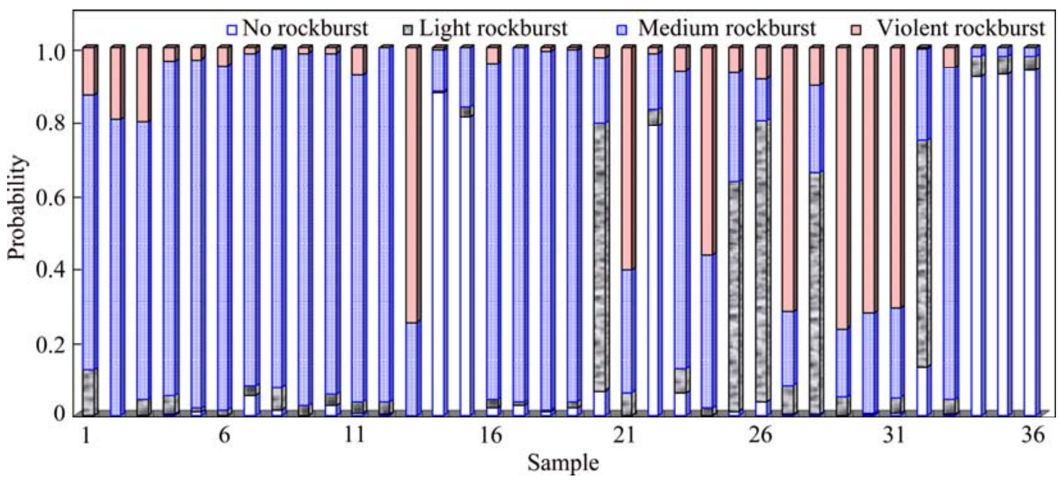

Fig. 1 Calculated results using RF model with index I for training samples

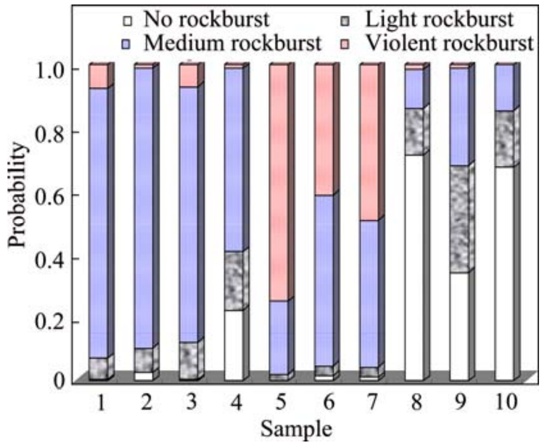

Fig. 2 Calculated results using RF model with index I for testing samples

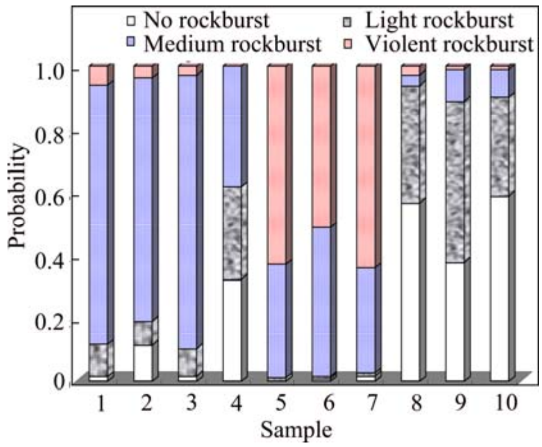

Fig. 3 Calculated results using RF model with index II for testing samples

4 Conclusions

1) Rockburst can be regarded as the dynamic instability process of the deformation system of sound stiff rock mass in high geostatic stress. The properties and the stress of surrounding rock are dominant factors for rockburst.

2) It is reasonable and feasible to choose index I including the maximum tangential stress in surrounding rock mass σ_θ, ratio of tangential stress of surrounding rock and uniaxial compressive σ_θ/σ_c, ratio of compressive rock strength and tensile strength σ_c/σ_t, and elastic energy index W_{et} as indexes to predict rockburst.

3) Misjudgment ratios of tested samples using RF, SVM and ANN are 0, 10% and 20%, respectively. Misjudgment ratios of training samples using RF, SVM and ANN are 0, 5% and 5%, respectively. The prediction results of both training and tested samples demonstrated that the developed RF model is effective and efficient approach to predict rockburst potential grade.

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岩爆等级预测的随机森林模型及应用

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摘 要：将随机森林分类方法应用于岩爆等级判定问题中。选用洞室围岩最大的切向应力、岩石单轴抗压强度、抗拉强度、岩石弹性能量指数作为岩爆等级判定的因素，并按照不同的组合形式将其分为指标组 I 和 II。以收集到的工程中的实际岩爆情况及数据作为训练样本，进行分析计算，建立岩爆等级判定的随机森分析模型。运用该分析模型对未参加训练的国内外工程实际岩爆情况进行判定，并与支持向量机及神经网络的判定结果进行比较。研究表明，指标组 I 优于指标组 II；用随机森林、支持向量机和神经网络方法计算的正确率分别为 100%、90%、80%。可见，随机森林方法判别能力强，误判率低，是解决岩爆等级判定的一条有效途径。

关键词：采矿工程；隧道工程；地下硐室；岩爆；随机森林

(Edited by Sai-qian YUAN)