Rock Mechanics and Rock Engineering: From the Past to the Future – Ulusay et al. (Eds)
© 2016 Taylor & Francis Group, London, ISBN 978-1-138-03265-1

Indexes sifting of rockburst prediction using soft science technology

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ABSTRACT: The rockburst hazard frequently occurs in the process of constructions with deeply buried rigid rock. It is a difficult problem that how to predict the occurrence and intensity of rockburst. General technologies often can not be competent because of the complex features of rockburst hazard assessment systems, such as multivariate, strong coupling and strong interference. So some soft science technologies often are employed, such as Support Vector Machines (SVMs). However, there is no determinated theory or method to sift indexes of rockburst prediction. This paper establishes several rockburst prediction models using SVMs. It indicated that stress coefficient σ_θ/σ_c, rock brittleness coefficient σ_c/σ_t and elastic energy index W_{et} are positive, while maximum tangential stress around tunnel σ_θ, uniaxial compressive strength of rock σ_c, uniaxial tensile strength of rock σ_t are negative. And the accuracy of rockburst prediction model with above three indexes reached 85%, which satisfied the need of actual projects.

1 INTRODUCTION

Rockburst is a kind of geotechnical disaster with dynamic failure. When surrounding rock is excavated in underground projects, elastic strain energy stored in rock mass is released suddenly which may cause blasting, flaking or launching of rock. The calamity of rockburst takes place frequently in the process of mining and tunnelling construction, which often causes a great number of casualties and monetary loss. A very intense rockburst , occurring in Jingping II hydropower station in 2010, caused 7 deaths and a TBM scrapped. (Qian 2014) Therefore, predicting rockburst effectively becomes an urgent problem that needs to be solved.

Many scholars nationally and internationally conduct a lot of research effort, and propose some rockburst predicting theories, such as Strength Theory, Rigidity Theory, Energy Theory, Rockbrust Tendency Theory, Instability Theory, Catastrophe Theory, Bifurcation Theory, Dissipative Structure theory, Chaos Theory and so on, which contributed for progress of rockburst prediction.

Due to the complex characteristics of rockburst predicting system including multivariate, strong coupling and strong interference, the prediction accuracy of above theories is not satisfactory. Under the circumstances, some scholars try to apply statistical theory and methods to rockburst prediction. Sun & Wang (2000) vividly calls it soft science methods, and lists it as one of achievements in rock mechanics. Soft science methods aiming at the predicting of rockbrust includes many kinds, this paper groups it into twelve categories. For example, Support Vector Machine Model (Feng & Zhao 2002), Artificial Neural Network Model (Sun et al. 2009), Comprehensive Fuzzy Mathematic Method (Wang et al. 1998), Unascertained Measure Model (Zhou et al. 2010), Extensible Comprehensive Evaluation Method (Xiong et al. 2007), Distance Discrimination Model (Gong & Li 2007), Rough Set Model (Wu & Chen 2014), Matter Element Model (Yang & Zhu 2000), Grey Theory (Jiang et al. 2003), Projection Pursuit Model (Xu & Xu 2010), Cloud Model (Liu et al. 2013) and Efficiency Coefficient Method (Wang et al. 2010).

Above soft science methods have a common characteristic which is the needing of choosing some geotechnical or mechanical parameters associated with rockburst. However, owing not to building up a consensus about rockburst mechanism, different people adopt different parameters, which is not in favor of a common rock-burst prediction model. Thus it is necessary to sift useful parameters according to previous studies and experience. This paper will sift useful parameters by using SVMs, and establish a common rockburst prediction model.

2 SUPPORT VECTOR MACHINES

Support Vector Machines (SVMs) were raised firstly by Vladimir & Vapnik (1995). Like Multilayer Neuro Network and Radial Basis Function Network, SVMs is used for pattern classification and nonlinear regression. SVMs can provide very good generalization performance in the aspect of pattern classification.

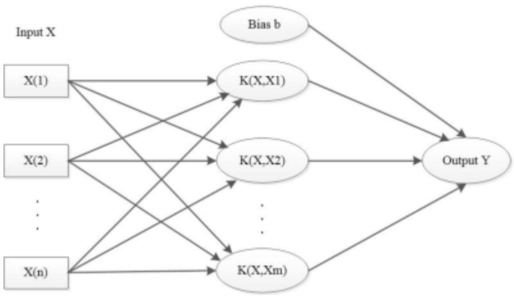

Figure 1. Support Vector Machines (SVMs) system structure.

SVMs system structure shows in figure 1. Here K represents kernel function which includes (1) linear kernel function: $K(x,x_i)=x^T x_i$, (2) polynomial kernel function: $K(x,x_i)=({}^T x_i+r)^p, \gamma>0$, (3) RBF kernel function: $K(x,x_i)=exp(\gamma\|xx_i\|2), >0$, (4) and two layer perceptron kernel function: $K(x,x_i)=tanh({}^T x_i+r)$. This paper selects RBF kernel function.

3 ROCKBURST PREDICTION MODELS

Maximum tangential stress (σ_s) reflects the stratum stress feature of rockburst area; uniaxial compressive strength (σ_c) and uniaxial tensile strength (σ_t) reflect the rock feature of rockburst area; elastic energy index (W_{et}) reflects the storing capability of elastic strain energy in rock. (Kidybiński 1981) By researching Russenes (1974), Turchaninov et al. (1972), Wang et al. (1998), Zhang and Fu (2008) and Hoek and Brown (1997) empirical criterion, the common feature is that stress coefficient (σ_θ/σ_c) is selected as an evaluation parameter. The rockburst criterion developed by Zhou et al. (2010) is that rockburst would occur when $\sigma_\theta/\sigma_c \geq K_s$, and that the value of K_s depends on rock brittleness coefficient (σ_c/σ_t). The smaller K_s is, the more severe rockburst is. Therefore, this paper takes maximum tangential stress around tunnel (σ_s), uniaxial compressive strength (σ_c), uniaxial tensile strength (σ_t), stress coefficient ($T_s=\sigma_\theta/\sigma_c$), rock brittleness coefficient ($B=\sigma_c/\sigma_t$) and elastic energy index(W_{et}) as six parameters to evaluate and predict rockburst strength, and to analyze the accuracy of prediction models through adopting different combination of parameters.

3.1 *The combination of parameters*

This paper collects 162 cases of rockburst by reading related literature. (Zhou et al. 2010) The data of T_s, B and W_{et} value is complete, while the number of cases in which all the parameters are completed is 108. There are 13 combinations designed in this paper.

(1) Combination 1: T_s, B, W_{et} (162 sets)
(2) Combination 2: T_s, B, W_{et}, σ_θ (108 sets)
(3) Combination 3: T_s, B, W_{et}, σ_c (108 sets)

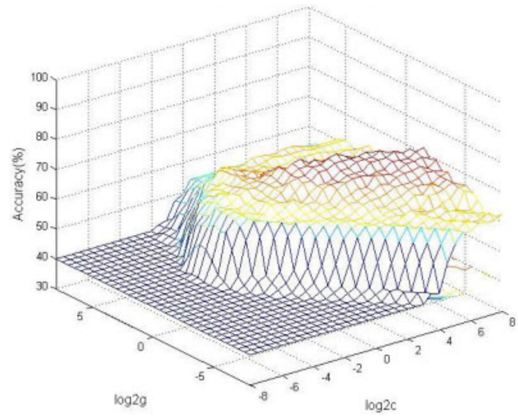

Figure 2. Cross-validation probability value after selecting SVC parameters.

(4) Combination 4: T_s, B, W_{et}, σ_t (108 sets)
(5) Combination 5: T_s, B, W_{et}, σ_θ, σ_c (108 sets)
(6) Combination 6: T_s, B, W_{et}, σ_θ, σ_t (108 sets)
(7) Combination 7: T_s, B, W_{et}, σ_c, σ_t (108 sets)
(8) Combination 8: T_s, B, W_{et}, σ_θ, σ_c, σ_t (108 sets)
(9) Combination 9: B, W_{et}, σ_θ, σ_c, σ_t (108 sets)
(10) Combination 10: T_s, W_{et}, σ_θ, σ_c, σ_t (108 sets)
(11) Combination 11: T_s, B, σ_θ, σ_c, σ_t (108 sets)
(12) (12) Combination 12: T_s (162 sets)
(13) Combination 13: σ_θ, σ_c, σ_t (108 sets)

3.2 *Prediction models and results*

3.2.1 *Combination 1: T_s, B, W_{et}*

142 cases are used as training set of prediction model, and other 20 cases are used as testing set.

Figure 2 shows that the value of cross-validation probability varys along with parameter c and g.

Figure 3 shows the comparison between predicted value and actual value in testing set. The circle mark represents the actual value, and the asterisk mark represents the predicted value. It can be seen from this picture that three predicted values are wrong among twenty sets.

The results of training set and testing set are (1) cross-validation probability value: $CVaccuracy=71.831\%$, (2) train set $accuracy=80.9859\%(115/142)$ (3) and test set $accuracy=85\%(17/20)$.

The details of prediction model of combination 1 are shown in Table 1.

3.2.2 *Other combinations*

The results of other twelve rockburst prediction models are listed in Tables 2 to 7. They are divided into six groups for convenient analysis.

(1) Combinations 2, 3 and 4

The results of combinations 2, 3 and 4 are shown in Table 2. Please note that c2 represents the combination 2, and other similar marks are roughly the same.

(2) Combinations 5, 6 and 7

The results of combinations 5, 6 and 7 are shown in Table 3.

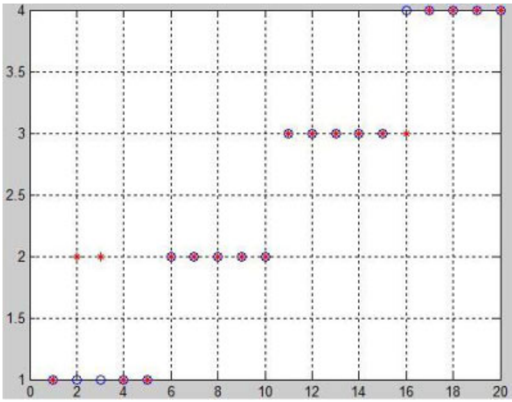

Figure 3. The predicted value vs. the actual value.

Table 1. The prediction result of combination 1.

Classification	Actual value	Predicted value
I	1	1
	1	2
	1	2
	1	1
	1	1
II	2	2
	2	2
	2	2
	2	2
	2	2
III	3	3
	3	3
	3	3
	3	3
	3	3
IV	4	3
	4	4
	4	4
	4	4
	4	4
Accuracy		85%

(3) Combination 8

The result of combinations 8 is shown in Table 4.

(4) Combinations 9, 10 and 11

The results of combinations 9, 10 and 11 are shown in Table 5.

(5) Combination 12

The result of combination 12 is shown in Table 6.

(6) Combination 13

The result of combination 13 is shown in Table 7.

4 DISCUSSION AND ANALYSIS

Some interesting phenomenon has been found through the training and testing of different combinations. This paper will discuss and analyze the prediction results of different combinations from six aspects. These work can reveal the reason behind the phenomenon, and some beneficial conclusions will be given out.

Table 2. The prediction result of combination 2, 3, 4.

Classification	Actual value	c2*	c3	c4
I	1	1	1	1
	1	2	2	2
	1	2	2	2
II	2	2	2	2
	2	2	2	2
	2	2	2	2
III	3	3	3	3
	3	3	3	3
	3	3	3	3
IV	4	3	3	3
	4	3	3	3
	4	3	3	4
Accuracy		58.33%	58.33%	66.67%

Table 3. The prediction result of combination 5, 6, 7.

Classification	Actual value	c5	c6	c7
I	1	1	3	1
	1	2	2	2
	1	2	2	2
II	2	2	2	2
	2	2	2	2
	2	2	2	2
III	3	3	3	3
	3	3	3	3
	3	3	3	3
IV	4	3	3	3
	4	3	3	3
	4	3	3	4
Accuracy		58.33%	50%	66.67%

Table 4. The prediction result of combination 8.

Classification	actual value	predicted value
I	1	3
	1	2
	1	2
II	2	2
	2	2
	2	2
III	3	3
	3	3
	3	3
IV	4	3
	4	3
	4	4
Accuracy		58.33%

4.1 *Analysis of combination 2, 3 and 4*

The common parameters included in 3 combinations are T_s, B and W_{et}. The accuracy of testing sets is (1) combination 2 (T_s, B, W_{et}, σ_θ): 58.33% (7/12), (2) combination 3 (T_s, B, W_{et}, σ_c): 58.33% (7/12) (3) and combination 4 (T_s, B, W_{et}, σ_t): 66.67% (8/12).

Table 5. The prediction result of combination 9, 10, 11.

Classification	Actual value	c9	c10	c11
I	1	2	3	3
	1	2	2	2
	1	2	2	2
II	2	3	1	2
	2	3	2	2
	2	3	2	2
III	3	3	3	3
	3	3	3	3
	3	3	3	3
IV	4	3	2	3
	4	3	2	3
	4	3	3	4
Accuracy		25%	41.67%	58.33%

Table 6. The prediction result of combination 12.

Classification	Actual value	Predicted value
I	1	2
	1	2
	1	2
	1	1
	1	1
II	2	2
	2	2
	2	2
	2	2
	2	2
III	3	3
	3	3
	3	3
	3	3
	3	3
IV	4	3
	4	3
	4	3
	4	3
	4	4
Accuracy		65%

The accuracy of models based on combinations 2, 3 and 4 is roughly consistent, and it is larger than 50%. So the contribution to the predicting model of σ_θ, σ_c and σ_t is roughly identical.

4.2 *Analysis of combination 5, 6 and 7*

This three combinations would explain the effect of σ_θ, σ_c and σ_t. The common parameters included in 3 combinations are T_s, B and W_{et}. The accuracy of testing sets is (1) combination 5 (T_s, B, W_{et}, σ_θ, σ_c): 58.33% (7/12), (2) Combination 6 (T_s, B, W_{et}, σ_θ, σ_t): 50% (6/12) (3) and combination 7 (T_s, B, W_{et}, σ_c, σ_t): 66.67% (8/12).

The accuracy of models based on combinations 5, 6 and 7 is also roughly consistent, and it is larger than 50%. So the contribution to the predicting model of σ_θ, σ_c and σ_t is roughly the identical.

Table 7. The prediction result of combination 13.

Classification	Actual value	Predicted value
I	1	3
	1	2
	1	2
II	2	2
	2	2
	2	3
III	3	3
	3	3
	3	3
IV	4	2
	4	2
	4	3
Accuracy		41.67%

4.3 *Analysis of combinations 9, 10 and 11*

The common parameters included in 3 combinations are σ_θ, σ_c and σ_t. The accuracy of testing sets is (1) combination 9 (B, W_{et}, σ_θ, σ_c, σ_t): 25% (7/12), (2) combination 10 (T_s, W_{et}, σ_θ, σ_c, σ_t): 41.67% (6/12) (3) and combination 11 (T_s, B, σ_θ, σ_c, σ_t): 58.33% (8/12).

We can see that the accuracy of predicting model based on combination 9 is lowest. It can be illustrated that the accuracy of predicting model will significantly decline without T_s. So T_s is a pivotal parameter for the rockburst prediction. That is why combination 12 is added in this paper. It's result is (4) combination 12 (T_s): 65%(13/20).

When only T_s is adopted, the accuracy is more than 60%, which also illustrates that T_s plays an important role in rockburst prediction.

The accuracy of predicting model based upon combinations 9, 10 and 11 successively lifts. That is to say the contribution of T_s is biggest and W_{et} smallest.

4.4 *Combinations 9, 10, 11 vs. combinations 5, 6, 7*

It can be seen that the accuracy of combinations 9, 10 and 11 is obviously lower than that of combinations 5, 6 and 7. That is to say the contribution of T_s, B and W_{et} is larger than σ_θ, σ_c and σ_t. Therefore, T_s, B and W_{et} are three parameters for predicting rockburst that we should place emphasis on.

4.5 *Combination 1 vs. combination 8*

The common parameters included in 2 combinations are T_s, B and W_{et}. The accuracy of testing sets (1) combination 1 (T_s, B, W_{et}): 85% (17/20) (2) and combination 8 (T_s, B, W_{et}, σ_θ, σ_c, σ_t): 58.33% (7/12).

Compared with combination 1, combination 8 has extra three parameters. But its accuracy decline greatly. So σ_θ, σ_c and σ_t are counter-productive. For further illustrating this view, this paper designs combination 13 only including σ_θ, σ_c and σ_t. It's result is (3) combination 13 (σ_θ, σ_c, σ_t): 41.67%(5/12).We can see that its accuracy is lower than 50%. This result responses above-mentioned view.

4.6 *Predicted value vs. Actual value*

(1) Apart from combinations 9, 10 and 13, the predicted values of rockburst classification II and III are all correct. We can find that in combination 9 the prediction result of rockburst classification II, without T_s, is all wrong; in combination 10 the prediction results error rate of rockburst classification II, without B, is 1/3; in combination 13 the predicting results error rate,without T_s, B and W_{et}, is also 1/3.

From this aspect, we can see that when T_s is added as one of the predicting parameters, the accuracy of predicting model for classification II and III rockburst is rather high.

(2) Apart from combination 1 and 12, the predicted values of rockburst classification I and IV are almost all wrong. We can find that in combination 1 the predicting resultâŁ™s accuracy of rockburst classification I and IV is 70%; in combination 12 the accuracy is 30%. Through observing these data carefully we can see that the common feature of combination 1 and 12 is that any one of σ_θ, σ_c and σ_t is excluded.

Therefore, we can draw a conclusion that all of σ_θ, σ_c and σ_t can seriously disturb the judgement of rockburst classification I and IV.

At the same time, only T_s considered (combination 12), the predicting accuracy of rockburst classification I and IV is only 30%, which is greatly lower than 70% of combination 1 (T_s, B, W_{et}). So for predicting rockburst of classification I and IV, value of T_s, B and W_{et} must been considered.

(3) In combination 1, the predicting accuracy of rockburst classification I and IV is 70%, which is lower than 100% of classification II and III. We think it is possible that there is misjudgement when experts identify rockburst classification by using of empirical method. So developing a practical quantitative standard is an important and urgent problem.

5 CONCLUSIONS

According to the above analysis, we can draw the following conclusions.

(1) In above-mentioned six parameters, stress coefficient T_s, rock brittleness coefficient B and elastic energy index W_{et} will influence the identification of rockburst classification, while maximum intensity of shear around tunnel σ_θ, uniaxial compressive strength σ_c and uniaxial tensile strength σ_t almost disturb the identification of rockburst classification I and IV.

(2) Among the three parameters including T_s, B and W_{et}, T_s is the most important one for predicting rockburst.

(3) In actual projects, there may be misjudgement when experts identify rockburst classification by utilizing empirical method.

(4) The predicting model of rockburst classification based upon combination 1 (T_s, B, and W_{et}) has rather high accuracy (85%), so it can be considered to implied into actual applications.

ACKNOWLEDGEMENT

The authors acknowledge the support of National Natural-Science Foundation of China (Grant No. 41072206) and the support of Science and Technology Project of Zhejiang Provincial Department of Transportation (No.2015J22).

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