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The Evaluation of Rockburst Risk Based on Modified Delphi Method

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Abstract: Rockburst is still a serious problem that has not been solved properly in rock mining and civil engineering construction. It would damage the lining structure and equipment such as the TBM, and even causes casualties and delays. Therefore, it has been a significant problem to forecast the occurrence of rockburst as well as to evaluate its risk. To this end, this paper puts forward a modified Delphi method. Meanwhile, three principal prediction indicators are selected. Additionally, the classification rule of the three indicators is confirmed by using the decision tree technique. Based upon this rule, the evaluating criteria of the possible rating of rockburst risk (namely P) is determined. In order to obtain the value of P according to the assessment of a panel of experts, the detailed risk evaluating procedure and technique for updating experts' weight values are proposed. In the process, the selectivity of experts is introduced, and the prediction of experts is derived according to the Bayes' theorem. And the attribute weight method is adopted, as the weights of above-mentioned prediction indicators need to be considered when calculating the prediction. Subsequently, a detailed calculation example is presented to interpret the modified Delphi method. Nevertheless, the subjectivity of the Delphi method is apparent, the objectivity evaluating rockburst risk can still be enhanced by utilizing above-mentioned tools and technique. Accordingly, the modified Delphi method can be applied into practical projects conveniently and effectively.

Keywords: modified Delphi method, rockburst risk, selectivity, prediction, Bayes' theorem

1. Introduction

From the perspective of Phenomenology, rockburst is a kind of phenomenon with breakage or shooting off of rock fragments accompanying with energy releasing violently. Authoritative scholars believe that the era of quantitative prediction of rockburst is coming (Qian 2014). The disasters caused by rockburst include casualties, equipment damage, delays in construction or production, higher construction costs and so on. Rockburst is a widespread calamity in rock mining and civil engineering construction. Even some mines go bankrupt due to the result of the excessive construction costs within rockburst region. Therefore, it is necessary to propose an effective method or to improve the exist technique to predict and then control the occurrence of rockburst. Demand becomes more urgent, especially the safety of construction in propensity stratum and rock mining needs to be ensured. Additionally, there is a strong rockburst in Jinping hydropower diversion tunnel at the depth of 2500m in November 28, 2010. (Qian 2014) That calamity caused 7 deaths and severe damage of a TBM.

Liu et al. (2013) studies the prediction of rockburst category by utilizing the cloud model and attribute weight method. Chen et al. (2014) obtains the weights of indicators used to predict rockburst by using of membership function back analysis. But the accuracy of rockburst prediction is not high according to these weights. Zhou et al. (2012) achieves the classification of rockburst rating by applying the support vector machines. However, this is a kind of black-box model, the relationship of each variable is unclear. Tang and Xia (2010) puts forward the concept of the ratio of the seismic stiffness of rock (namely dS/dt) by researching the seismic events accompanying rockburst. The possibility of a rockburst would increase if dS/dt>0, otherwise it would decrease. Qiu et al. (2011) predicts rockburst according to the real-time monitoring microseismic events in projects, and proposes a kind of experience assessment method namely rockburst vulnerability index (*RVI*) to predict the depth rockburst pit.

In view of the characteristics of rockburst including multi-variable, strong coupling and strong interference, it is very difficult to grasp fully the mechanism of rockburst just according to abovementioned techniques. In addition the possibility of rockburst occurrence can be predict on the basis of experts' experience. In this respect, this paper puts forward a modified Delphi method to predict the possibility of rockburst occurrence.

2. Evaluating criterion

Rockburst often accompany with some special phenomenon, such as rock failure, rock debris spalling, acoustic emission, which often is viewed as the empirical classification criteria of rockburst intensity.

However, in order to conduct the prediction of rockburst more precisely, the quantitative classification criterion must be determined. Below the decision tree classifier will be used to obtain the quantitative classification criteria of rockburst intensity.

2.1 Decision tree classifier models

By referring to the related scholars' research, this paper chooses three indicator as the main parameters, including stress coefficient $Ts=\sigma_\theta/\sigma_c$, rock brittleness coefficient $B=\sigma_c/\sigma_t$ and elastic energy index W_{et}.

The prerequisites using decision tree is gathering some cases of rockburst to train the model. In conclusion, a total of 162 cases are collected to train the model built with decision tree classifier. (Jiang et al. 2010, Xu and Xu 2010) Among these cases, 142 cases are regarded as training data set, while another 20 ones are regarded as testing data set. Subsequently, the decision tree classifier models about three indicators are built.

Fig. 1 shows the decision tree classifier model about the attribute *Ts*. The quantity of x1 represents the value of this attribute. Thus the value range of the attribute *Ts* corresponding to the rockburst intensity is easy to obtain. Another two attributes' value range can also be achieved by this means. All results are recorded in Table 1.

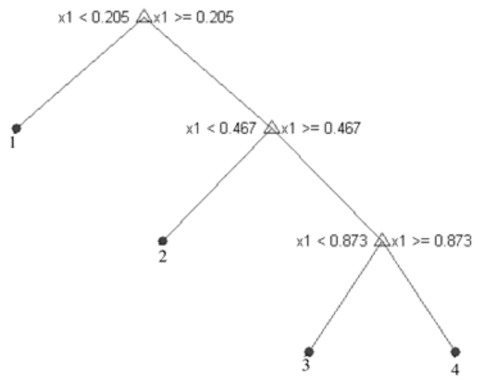

Figure 1. Decision tree classifier model

2.2 The evaluating criteria of P

By summarizing the value range of three indicators, and adding corresponding evaluating score range, the evaluating indicators could be obtained. The result is recorded in Table 1.

Table 1. The evaluating indicator of the possible rating of rockburst risk (namely P)

ID	The evaluating indicator	Value range	Score
A	Stress coefficient $Ts=\sigma_\theta/\sigma_c$	$Ts<0.205$	0～5
		$0.205\leqslant Ts<0.467$	6～10
		$0.467\leqslant Ts<0.873$	11～15
		$Ts\geqslant 0.873$	16～20
B	Rock brittle coefficient $B=\sigma_c/\sigma_t$	$B\geqslant 61.268$	0～5
		$26.25\leqslant B<61.268$	6～10
		$14.265\leqslant B<26.25$	11～15
		$B<14.265$	16～20
C	Elastic energy index W_{et}	$W_{et}<1.96$	0～5
		$1.96\leqslant W_{et}<3$	6～10
		$3\leqslant W_{et}<6.4065$	11～15
		$W_{et}\geqslant 6.4065$	16～20

Then the evaluation rate is given in Table 2. The calculating method of the calculating score *R* would be introduced in Section 3.

Table 2. The evaluation rating

Calculating score *R*	Description	Rating
15～20	Very likely	4
10～15	Possible	3
5～10	Accidentally	2
0～5	Impossible	1

3. Evaluation process in panel & determination and updating of experts' weight

The Delphi method has a weakness with strong subjectivity. However, the experience of experts still has great reference value before the mechanism of ruckburst has been grasped clearly. So as to make the survey result with the Delphi method respond to the rockburst law more objectively, this paper introduces two concepts of selectivity and prediction. And the cloud model (Liu et al. 2013) is used to calculate the probability of influential relationship of each evaluating indicator.

3.1 Selectivity

Expert's selectivity consists of two aspects namely sensitivity and specificity, and their expression is as follows. (Haimes 2004)

(1) Sensitivity of an individual judgment α_i^+ = P(+*i*|*INF*) = the conditional probability that an expert judges the relationship to be influential given that there exists an influential relationship.

(2) Specificity of an individual judgment α_i^- = P(-*i*|*UINF*) = the conditional probability that an expert judges the relationship to be uninfluential given that there does not exists an influential relationship.

The symbol +*i* represents an expert judges the relationship to be significant, –*i* represents the expert's judgment of insignificant relationship and *INF*, *UINF* represent the influential relationship and the uninfluential relationship, respectively.

Eq. (1) expresses the initial weight of the *j*th expert, that can be calculated by using the selectivity values of n experts.

$$w_i = \frac{\alpha_i^+ + \alpha_i^-}{\sum_{k=1}^{n}\left(\alpha_k^+ + \alpha_k^-\right)}, \quad k = 1,2,\cdots,n; \quad \boldsymbol{i}=1,2,\cdots,\boldsymbol{n} \tag{1}$$

where α_k^+ and α_k^- are sensitivity and specificity of the kth expert, respectively.

3.2 Prediction

The prediction expressed by Eq.(2) and Eq.(3) can be calculated according to the Bayesian Theory.

$$\begin{aligned}\beta_{ij}^+ &= P\left(INF_j \mid +i\right) \\ &= \frac{P\left(+i|INF_j\right)P\left(INF_j\right)}{P\left(+i \mid INF_j\right)P\left(INF_j\right)+P\left(+i \mid UINF_j\right)P\left(UINF_j\right)} \\ &= \frac{\alpha_i^+ P\left(INF_j\right)}{\alpha_i^+ P\left(INF_j\right)+\left(1-\alpha_i^-\right)P\left(UINF_j\right)},\end{aligned} \tag{2}$$

i=1, 2, ⋯, n; j=1, 2, ⋯, m

$$\begin{aligned}\beta_{ij}^- &= P\left(INF_j \mid -i\right) \\ &= \frac{P\left(-i \mid INF_j\right)P\left(INF_j\right)}{P\left(-i \mid INF_j\right)P\left(INF_j\right)+P\left(-i \mid UINF_j\right)P\left(UINF_j\right)} \\ &= \frac{\alpha_i^- P\left(INF_j\right)}{(1-\alpha_i^+)P\left(INF_j\right)+\alpha_i^- P\left(UINF_j\right)},\end{aligned} \tag{3}$$

$\boldsymbol{i}$= 1, 2, ⋯, $\boldsymbol{n}$; $\boldsymbol{j}$= 1, 2, ⋯, $\boldsymbol{m}$

The symbols β_{ij}^+ and β_{ij}^- represent the probability of evaluating indicator *j* which is influential on the condition of *i*th expert's judgement. The symbol *m* represents the number of evaluating indicators. The symbols P(INF_j) and P($UINF_j$) represent the probability of influential relationship and the probability of uninfluential relationship, respectively. Note that P(INF_j) + P($UINF_j$) = 1. The values of P(INF_j) and P($UINF_j$) will be determined by using the cloud model method. The detail calculation process will be introduced in Section 4.

Then the prediction weight of an individual expert can be calculated by using Eq. (4).

$$w_{ij} = \frac{\beta_{ij}^+ + \beta_{ij}^-}{\sum_{k=1}^{n}\left(\beta_{kj}^+ + \beta_{kj}^-\right)} \tag{4}$$

3.3 The judgment of expert panel

Let X_{ij} be a random variable which represents the judgment of the *i*th expert to the *j*th indicator. Then X_{ij} = 0～20.

Let C_i denote the *i*th combination of *n* individual judgments. Then

$$C_i = \left\{x_{i1}, x_{i2}, \cdots, x_{ik}, \cdots x_{im}\right\}, \quad i = 1,2,\ldots,\boldsymbol{n}; \quad k = 1,2,\ldots,m \tag{5}$$

The symbol *m* represents the number of evaluating indicators. The judgment result of the *i*th expert can be calculated as follows.

$$R_i = \sum_{j=1}^{m} w_{ij} x_{ij}, i = 1, 2, \cdots, \text{n};\ j = 1, 2, \cdots, m \quad (6)$$

Then the calculation score of expert panel can be calculated as follows.

$$R = \sum_{i=1}^{n} w_i R_i \quad (7)$$

Then the value of P (the possible rating of rockburst risk) can be given according to Table 1.

3.4 The updating of experts' weight

The error and its percent between the judgment result of an individual expert and the judgment result of expert panel can be calculated by using Eq. (8) and Eq. (9).

$$err_i = | R_i - R |, i = 1, 2, \cdots, n \quad (8)$$

$$percent(err_i) = \frac{err_i}{\sum_{k=1}^{n} err_k}, \quad k = 1, 2, \cdots, n;\ \ i = 1, 2, \cdots, n \quad (9)$$

Then experts' weight after updating can be calculated as follows.

$$w_i^{'} = \frac{w_i \times [1 - percent(err_i)]}{\sum_{k=1}^{n} w_k \times [1 - percent(err_k)]}, \quad k = 1, 2, \cdots, n;\ \ i = 1, 2, \cdots, n \quad (10)$$

Fig. 2 shows the flow of panel judgement and the updating of experts' weight values base upon Bayes' theorem.

4. The determination of the probability of influential relationship of indicators

Calculating the probability of influential relationship of indicators (namely P(*INF*)) by utilizing of the attribute weight method (Jiang et al. 2010) according to the above-mentioned 162 rockburst cases in the session 2. Table 3 lists some statistical parameters and entropy parameters of indicators for rockburst class I. Another three classes' statistical parameters can be calculated in the same means, which would not be listed here.

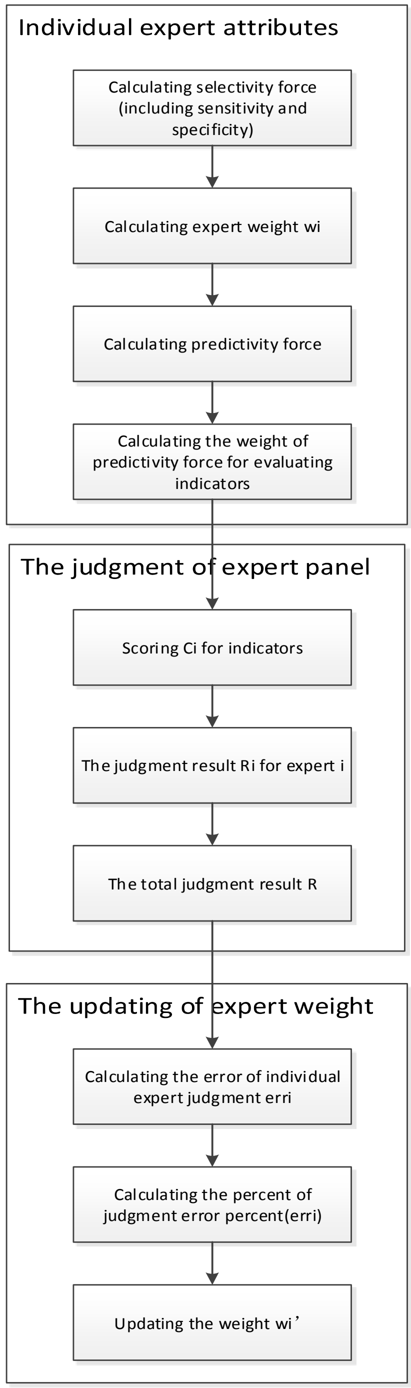

Figure 2. The flow chart of panel judgment and updating of experts' weight values based upon Bayes' theorem

Table 3. The calculating parameters about rockburst class I

Class I	σ_θ	σ_c	σ_t	σ_θ/σ_c	σ_c/σ_t	W_{et}
Number of cases	18	18	18	26	26	26
Number of missing values	8	8	8	0	0	0
Minimum value	2.60	18.32	0.38	0.05	6.67	0.01
Maximum value	107.50	178.00	10.90	0.72	79.99	7.80
Mean value	27.31	79.96	4.26	0.21	38.44	2.22
Mean square deviation	28.29	51.03	2.44	0.14	26.05	2.32
Entropy Ensj (former)	8.24	20.55	1.29	0.05	10.59	0.73
Entropy Ensj (latter)	26.73	32.68	2.21	0.17	13.85	1.86

Table 4 lists the probability of influential relationship of rockburst indicators.

Table 4. The probability of influential relationship of rockburst risk prediction indicators

Indicators	σ_θ	σ_c	σ_t	σ_θ/σ_c	σ_c/σ_t	W_{et}
P(*INF*)	0.1014	0.0226	0.0085	0.4776	0.1351	0.2548

Fig. 3 plots the probability of influential relationship of rockburst indicators vividly. As can be seen from the figure, three indicators including σ_θ/σ_c, σ_c/σ_t and W_{et} play more important roles in rockburst predication, while another three indicators including σ_θ, σ_c and σ_t can be omitted. Therefore, the indicators σ_θ, σ_c and σ_t are excluded and the original ratio of the retaining three indicators remain unchanged. Then the probability of influential relationship of the retaining three indicators are calculated. Table 5 lists the calculation result.

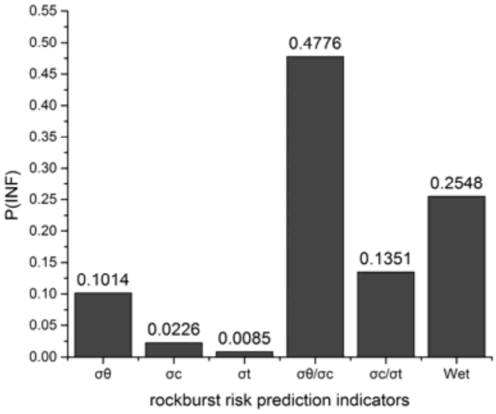

Figure 3. The probability of influential relationship of rockburst indicators

Table 5. The modified relative importance of rockburst risk prediction indicators

Indicators	σ_θ/σ_c	σ_c/σ_t	W_{et}
P(*INF*)	0.5505	0.1558	0.2937

5. Example

5.1 Attributes of experts

Assuming eight experts were invited to participate in this research. Table 6 lists the selectivity and weight values of experts. Table 7 lists the prediction of experts.

Table 6. The assumed selectivity and weight values of experts

Expert id	α_i^+	α_i^-	w_i
1	0.8911	0.6808	13.01%
2	0.5442	0.4851	8.52%
3	0.9370	0.8851	15.08%
4	0.8051	0.8595	13.78%
5	0.7226	0.9429	13.79%
6	0.7187	0.6521	11.35%
7	0.9424	0.7380	13.91%
8	0.6735	0.6020	10.56%

Table 7. The assumed prediction of experts

Expert id	σ_θ/σ_c	σ_c/σ_t	σ_c/σ_t
1	50.38%	18.28%	31.34%
2	50.20%	18.40%	31.39%
3	44.22%	22.82%	32.96%
4	40.97%	25.59%	33.44%
5	48.26%	19.71%	32.03%
6	43.09%	23.58%	33.33%
7	45.13%	21.91%	32.96%
8	46.90%	20.60%	32.50%

5.2 Panel judgement and the updating of experts' weight values

Table 8 lists the result of panel judgement. As can be seen from the result, the possible rating of rockburst is III. And table 9 lists experts' weight values after updating.

Table 8. The result of panel judgement

expert	σ_θ/σ_c	σ_c/σ_t	σ_c/σ_t	R_i
1	5	15	17	10.59
2	10	14	14	11.99
3	6	14	18	11.78
4	16	19	9	14.43
5	15	15	6	12.12
6	13	16	12	13.37
7	16	13	18	16.00
8	13	13	12	12.67
			R	***12.98***
			P	***3***

Table 9. Experts' weight values after updating

expert	error	original weight	updating weight
1	2.3937	10.94%	***9.67%***
2	0.9912	10.85%	11.23%
3	1.2023	12.76%	12.92%
4	1.4437	14.27%	14.08%
5	0.8654	11.46%	12.02%
6	0.3912	13.91%	15.30%
7	3.0187	13.25%	***10.83%***
8	0.3081	12.56%	13.93%

As can be seen from the result that the weighted values of 1st and 7th expert are decreased owing to the larger error.

6. Conclusions

Based on the work above, conclusion can be made as follows.

(1) Combining the rockburst cases, the class ranging of rockburst risk prediction indicators can be obtained conveniently by utilizing of the decision tree classifier.

(2) The probability of influential relationship of rockburst risk prediction indicators can be obtained by using of the attribute weight method.

(3) The flow of panel judgement and the updating of experts' weight values are improved.

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