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ORIGINAL PAPER

Prediction of rock burst in underground caverns based on rough set and extensible comprehensive evaluation

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Abstract In high terrestrial stress regions, rock burst is a major geological disaster influencing underground engineering construction significantly. How to carry out efficient and accurate rock burst prediction is still not resolved. In this paper, a new rock burst evaluation method based on rough set theory and extension theory is proposed. In the method the following seven indexes were selected as indices to evaluate and predict rock bursts: uniaxial compressive strength, ratio of rock strength to in situ stress, ratio of rock compressive strength to tensile strength, ratio of tangential stress and rock compressive strength, elastic strain energy index, depth of tunnel, and rock integrity. According to rough set theory, those indexes influencing rock bursts were investigated through attribute reduction operation to obtain four main influential indexes and the weight coefficients of each evaluation index were acquired by analysing the significance of conditional attribute. Thereafter, the main influential indexes and its weight were taken into the extension theory to predict the practical engineering. This method was applied to a practical case, underground caverns of Jiangbian hydropower station in China's Sichuan province. It is proved that the evaluation results of the method were well consistent with real conditions.

Keywords Rock burst prediction · Rough set theory · Extension theory · Underground caverns

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Introduction

With the rapid development of economic construction, geotechnical engineering is developing extensively, especially in the nuclear industry, transportation, water conservancy, and other industries. The scale and depth of underground engineering are both rapidly growing. With the increasing depth of underground engineering, the possibility of occurrence of engineering disasters also increased, especially rock burst induced by high terrestrial stress (Lee et al. 2004; Gu et al. 2002; Jiang et al. 2010). As a typical failure phenomenon, rock burst often occurs in a sudden or violent way in the excavation surface of underground rock masses. The occurrence of rock burst directly threatens the safety of personnel and equipment, seriously affecting the progress of the project, and has become a worldwide problem of underground engineering.

The theoretical research of rock burst was first carried out in the 1920s. Since then, different scholars have analysed the mechanism of rock burst from different angles. The representative theories include strength theory, energy theory, stiffness theory, fracture damage theory, and dynamic perturbation theory (Cook et al. 1966; Ortlepp and Stacey 1994; He et al. 2010). In recent years, a large number of scholars have studied the mechanism of rock burst from unloading test, model test, dynamic and static characteristics of rock burst. For instance, on the basis of unloading tests involving different stress paths, Chen et al. (2010) studied the energy release rules and characteristics of rock and proved that the faster the unloading rate, the stronger the brittle failure and the greater the possibility of rock burst. Zhang et al. (2012a, b) tested the acoustic emission parameters of marble specimens under triaxial compression test and destruction process of unloading confining pressure and studied the difference of acoustic emission characteristics between the two stress paths of loading and unloading.

In recent years, scholars have used mathematical statistics and experimental methods to predict the occurrence of rock burst. Feng and Zhao (2002) established a support vector machine model to predict rock burst. In view of the complexity of rock burst problems, Su and Feng (2005) evaluated rock burst failure in underground caverns using an elastic–brittle–plastic mechanical model under high stress and energy release rate indexes. Jiang et al. (2004) built the dynamically weighted grey optimization model and applied it to forecast rock burst risks on the western route of the South–North Water Transfer Project. Xu and Xu (2010) established a projection pursuit model based on particle swarm optimization for rock burst prediction. Gong and Li (2007) 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. Dong et al. (2013) 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. (2016) adopted the method of cloud model with entropy weight to predict and classify rock burst. Li et al. (2017) used a novel application of Bayesian networks (BNs) to predict rock burst. Jia et al. (2015) proposed an assessment approach to assess the likelihood of rock burst in coal mines by integrating the multi-agent system with data fusion techniques. Li et al. (2016) studied the characteristics of micro-seismic (MS) waveforms prior to and during the rock burst, and provided a new research idea to predict rock burst. However, these methods provide some scientific judgment for the prediction of rock burst, but it is undeniable that these methods still have some shortcomings. The complexity of practical projects and difference in various geological conditions meant that existing methods for predicting rock burst cannot meet the demands of practical projects. Therefore, the introduction of a new intelligent method for the research of rock burst and intensity classification prediction is still very necessary.

In this paper, a new rock burst evaluation method based on rough set theory and extension theory is proposed. Firstly, the influence factors of rock burst are analyzed by attribute reduction operation in rough set theory, and obtain the main influencing factors of rock bursts. Then the weight coefficients of each evaluation index are acquired by analysing the significance of conditional attribute. Thereafter, the main influential indexes and its weight were taken into the extension theory to predict the practical engineering. This method was applied to a practical case, underground caverns of Jiangbian hydropower station in China's Sichuan province. It is proved that the evaluation results of the method were consistent well with real conditions.

Overview of the project

Jiangbian hydropower station is located on the lower reaches of the Jiulong River, which is the first tributary on the left bank of the Yalong River, in the southeast of Ganzi Tibetan Autonomous Prefecture, Sichuan, China (Fig. 1). It is the last cascade of hydropower stations included in the development plan for one reservoir and five cascades of hydropower stations for Jiulong River. The station is a dam-diversion scheme and the main buildings comprise: head of pivot, water diversion system, and underground power house. It is a secondary hydropower engineering asset, with a total reservoir capacity of 1.33 million m^3 and a total installed capacity of 330 MW. The underground powerhouse caverns primarily consist of a main powerhouse, main transformer chamber, tailrace tunnel, and draft tube gate chamber, with a burial depth of 160–220 m. The excavation dimensions of the main powerhouse were designed to be 100 m length, 17.5 m width, and 44.2 m height. The elevation of vault is 1518.35 m. The axis of the powerhouse is N15°W. The main powerhouse and the main transformer chamber are arranged in parallel and the axis distance between two chambers is 47.8 m, the excavation dimensions were designed as 71.3 length, 13.6 width, and 23.6 m height; the vault elevation reaches 1517.1 m. And design excavation size of tail chamber is 61 m length, 6.5 m width, and 13.9 m height, with a vault elevation of 1526.3 m.

Three-dimensional relative position of the underground powerhouse caverns and mountain is shown in Fig. 2, and the structure of hydropower station is shown in Fig. 3.

The geological conditions of the region of the underground powerhouse caverns are relatively simple, The bedrock is Yanshanian biotite granite, with hard rock, single lithology and moderate weathering, The rock mass is intact-comparatively intact and its quality is considered

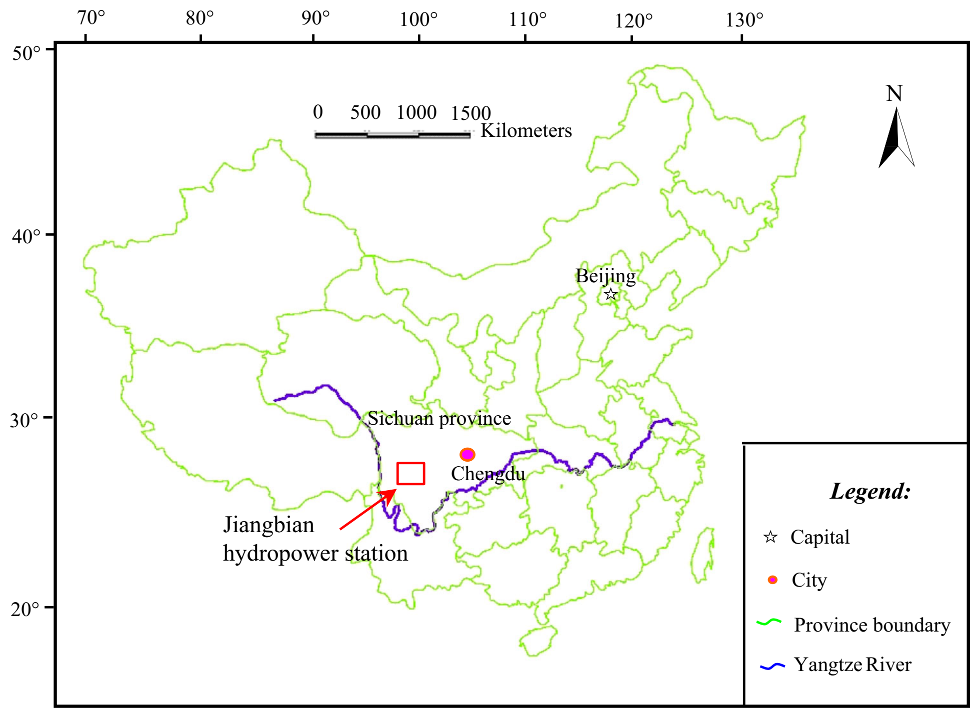

Fig. 1 Geographical position of the Sichuan Jiangbian hydropower station

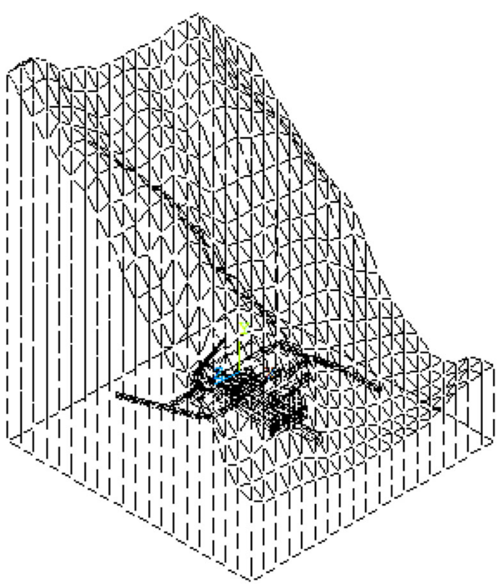

Fig. 2 Relative position of the underground powerhouse caverns and mountain

fair-good. The fault is rare and the scale is not large, the structural plane is not developed, the joint surface is good and closed, so it don't have a great impact on the stability of surrounding rock. The maximum principal stress is 14 MPa (the depth is 302 m), which is in the area of high ground stress. The groundwater is not developed.

At the beginning of construction of the traffic tunnel of the underground powerhouse tunnel, slight-moderate rock bursts (Fig. 2) occurred frequently (Fig. 4), and strong rock bursts occurred several times (Fig. 2) during the excavation of the high-pressure water diversion tunnel (Fig. 5).

Method

Rough set theory

Rough set theory as a mathematical method was proposed by Pawlak (1982) to process incomplete and inaccurate data. Prior knowledge is not required in the solution of complex geotechnical engineering problems based on this theory, merely those data in the decision table are necessary.

Connotation of knowledge

According to rough set theory, knowledge refers to classification ability, namely, knowledge is the classification of data (Greco et al. 2001). By introducing the concept of a set, the discrete expression of space U is classified by equivalent relation set R; knowledge is the classification result of U by R. Therefore, in the senses of U and R, knowledge base K is defined as the classification of U by all possible relationships in R, which is denoted as:

$$K = (U, R). \quad (1)$$

When a set of data U and the equivalent relation set R are given, the classification of U by R is defined as knowledge, which is denoted as U/R. On this basis, and

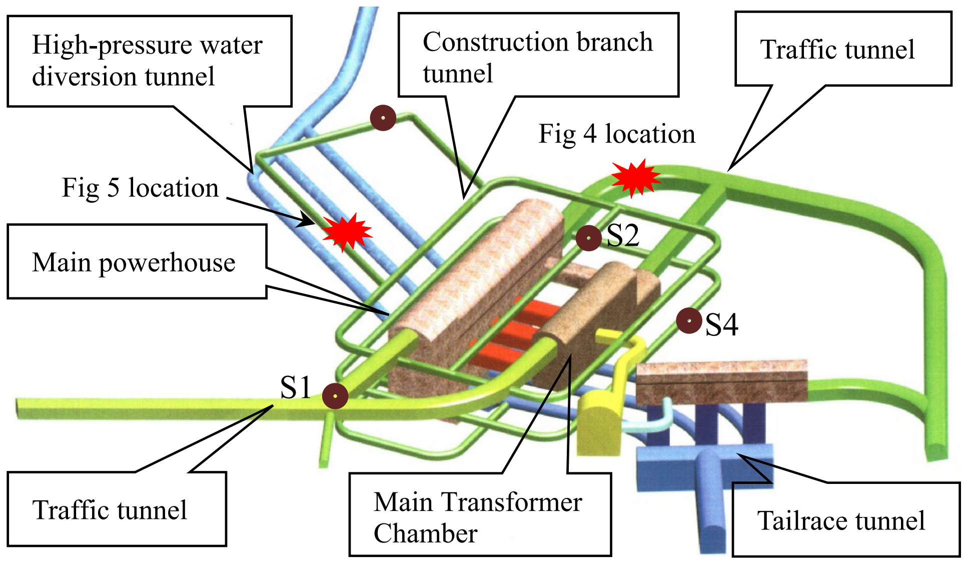

Fig. 3 Structure of Jiangbian hydropower station

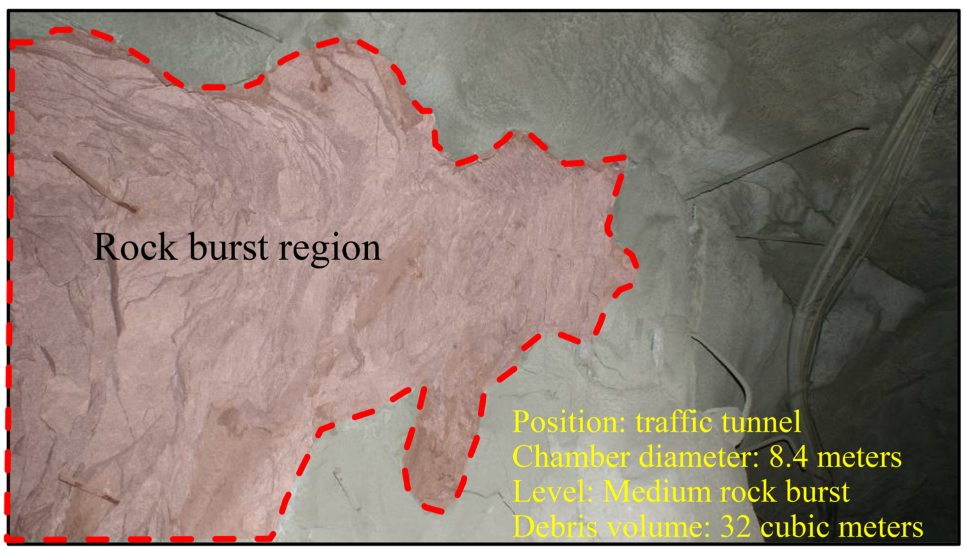

Fig. 4 Typical rock burst in the traffic tunnel

concerning the rock burst problem in this research, U is a sample set of rock bursts, equivalent relation set R is the classification of the sample set of rock bursts. In this research, rock bursts are classified into four grades. Thus, knowledge base K refers to the sample set classified according to different grades of rock burst.

Decision table and attribute dependency degree

Information systems are a form of knowledge expression. The mode of knowledge expression is important in intelligent data processing. Information systems are also called knowledge expression systems.

Formally, a quaternion $S = (U, A, V, f)$ is an information system, where U is the non-empty finite set of objects, namely, the universe; A is the non-empty finite set of attributes; $V = \cup_{a \in A} V_a$, where V_a is the range of attributes; $f : U \times A \rightarrow V$ is an information function in which each attribute of each object is endowed with an information value, that is, $\forall a \in A$, $x \in U$, and $f(x, a) \in V_a$.

Where $A = C \cup D$ and $C \cap D = \Phi$; C denotes the condition attribute set; and D is the decision attribute set. The knowledge expression system, with both condition and decision attributes, is a decision table.

If $U/C = \{X_1, X_2, \ldots, X_n\}$, which implies that by classifying the set U using all possible relationships in condition attribute set C, the obtained X_n is also a set included in the aforementioned classification.

If $U/D = \{Y_1, Y_2, \ldots, Y_m\}$, this indicates that when classifying set U using all possible relationships in decision attribute set D, the acquired Y_m also expresses a set covered in the aforementioned classification.

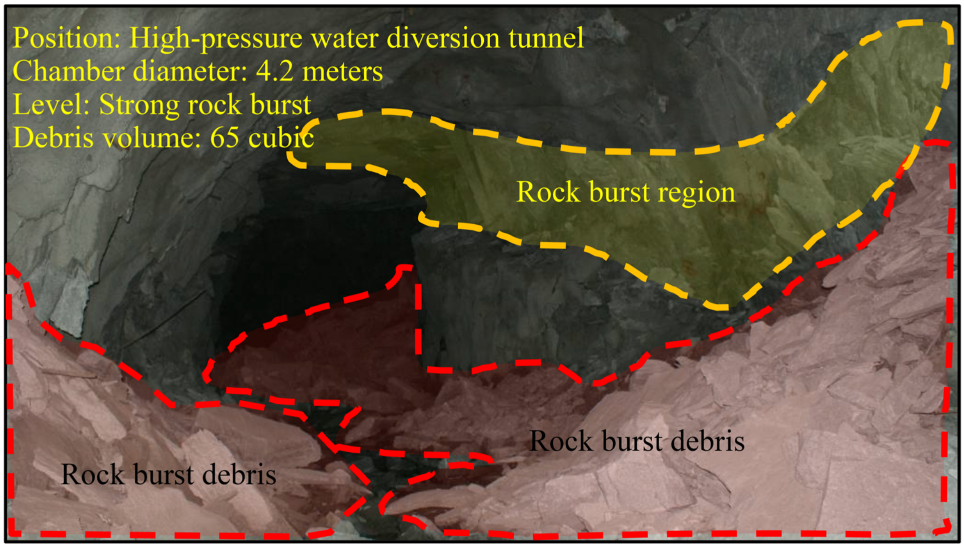

Fig. 5 Strong rock bursts in the high-pressure water diversion tunnel

$$\text{If} \quad k = \gamma_C(D) = \frac{1}{|U|}\sum_{i=1}^{m} |\gamma_C(D_i)|, \quad Y_i \in U/D. \tag{2}$$

$|U|$ is the number of samples in set U. Therefore, the dependencey degree of decision attribute set D on condition attribute set C is associated with the value of k. When $k = 1$, D is completely dependent on C; if $0 < k < 1$, D is partially dependent on C; when $k = 0$, D is totally independent of C.

Attribute reduction

Reduction is to remove unrelated and redundant knowledge without changing the classification ability of the knowledge base. Reduction and kernel are two basic concepts of attribute reduction. In the decision table, attribute reduction refers to the reduction of decision rules, namely, removing redundant attribute values in expression of the rules. Attribute reduction and kernel are the core and among the most important concepts of rough set theory. They provide a method of analysis for redundant attributes and realise the reduction of knowledge through reduction of attribute values in the decision table (Chen et al. 2007).

The significance of attributes and the weight of evaluation indices

In the decision table, different attributes are of varying significance. To explore the significance of certain attributes, the classification variations without such attributes are observed by removing these attributes. If the corresponding classification varies significantly without a certain attribute, this indicates a high intensity of the attribute, that is, the attribute is significant: on the other hand, it shows that the attribute is of low intensity and less significance if the opposite were true. Therefore, the significance degree of condition attribute C_i related to decision attribute D is defined as:

$$\sigma_{CD}(C_i) = \gamma_C(D) - \gamma_{C-C_i}(D), \tag{3}$$

$$\gamma_{C-C_i}(D) = \frac{1}{|U|}\sum_{i=1}^{m} \left|\gamma_{C-C_i}(D_i)\right|. \tag{4}$$

The greater the value of $\sigma_{CD}(C_i)$, the more significant the attribute C_i in the whole condition attribute set.

According to rough set theory, the weight coefficient of the index is obtained as follows (Zhang et al. 2009):

1. Based on Eq. (2), the dependency degree of decision attribute set D on all condition attributes in C ($\gamma_C(D)$) was calculated;
2. Regarding each evaluation index C_i, the dependency degree of decision attribute set D on condition attributes $C - C_i(\gamma_{C-C_i}(D))$ was obtained according to Eq. (4);
3. According to formula (3), calculate the significance $\sigma_{CD}(C_i)$ of each evaluation index C_i.
4. Get the weighting coefficient of evaluation index C_i by formula (5) below.

$$\alpha_i = \frac{\gamma_{C-C_i}(D)}{\sum_{j=1}^{n} \gamma_{C-C_i}(D)} \quad (i = 1, 2, \ldots, n). \tag{5}$$

Extension theory

Extension theory is often used to solve incompatibility and contradiction problems (Jun 2009; Wang et al. 2009). For example, an object is influenced by several factors; if we analyse only a single factor, then the object fits in one category; analysing the object using another factor results in it being classified in a different category. Extension theory can thus be used to rank factors. The theory is based on the matter element model and extension set theories (Cai 1997; Ye 2009). In addition, extension theory can be used to describe the thinking process associated with both quantitative and qualitative analyses and to express varied knowledge to obtain a standardized representation of such knowledge. This theory tries to solve the incompatibility or contradiction of problems by transforming the matter–element. The matter–element is the logic cell of the extenics and is the basic element for describing things represented by $R = (N, C, V)$, where N represents the matter, C represents the characteristics of the matter, and V represents the measure of N with respect to the characteristic C. The specific steps for the assessment can be described as follows.

The determination of the classical field

$$R_{0j} = (N_{0j}, C, V_{0ji}) = \begin{bmatrix} N_{0j} & c_1 & V_{0j1} \\ & c_2 & V_{0j2} \\ & \cdots & \cdots \\ & c_n & V_{0jn} \end{bmatrix} = \begin{bmatrix} N_{0j} & c_1 & \langle a_{0j1}, b_{0j1} \rangle \\ & c_2 & \langle a_{0j2}, b_{0j2} \rangle \\ & \cdots & \cdots \\ & c_n & \langle a_{0jn}, b_{0jn} \rangle \end{bmatrix}, \tag{6}$$

where N_{0j} denotes classified rock burst grade of j $(j = 1, 2, 3, \ldots, m)$; $c_i (i = 1, 2, 3, \ldots, n)$ refers to the factor influencing rock burst grade N_{0j}; $V_{0ji} = \langle a_{0ji}, b_{0ji} \rangle$ is the value range of N_{0j} relating to factor c_i, namely, the data range of rock burst grade associated with the corresponding evaluation factor, which is defined as the classical field.

The establishment of the sectional field

$$R_p = (P, C, V_p) = \begin{bmatrix} P & c_1 & V_{p1} \\ & c_2 & V_{p2} \\ & \cdots & \cdots \\ & c_n & V_{pn} \end{bmatrix} = \begin{bmatrix} N_{0j} & c_1 & \langle a_{p1}, b_{p1} \rangle \\ & c_2 & \langle a_{p2}, b_{p2} \rangle \\ & \cdots & \cdots \\ & c_n & \langle a_{pn}, b_{pn} \rangle \end{bmatrix}, \tag{7}$$

where P represents all rock burst grades; $V_{pi} = \langle a_{pi}, b_{pi} \rangle$ is the value range of P related to factor i, that is, the sectional field of P.

The determination of matter (elements) for evaluation

Concerning the cavern section under evaluation p, evaluation matter element R was acquired by expressing the collected data or analysis results as matter elements.

$$R = (P, C, v_i) = \begin{bmatrix} P & c_1 & v_1 \\ & c_2 & v_2 \\ & \cdots & \cdots \\ & c_n & v_n \end{bmatrix}, \tag{8}$$

where P is the cavern section under evaluation; c_i denotes the factor influencing rock burst grade; v_i is the value of P related to factor c_i, which refers to the data from the cavern section under evaluation.

The calculation of weight coefficient

Weight coefficient, which reflects the significance of an index to the evaluation results, was calculated using rough set theory.

Construction of the correlation between the evaluation index and rock burst grade

The extent of any correlation between individual evaluation indices of each cavern section (v_i) with rock burst grade (j) is

$$K_{0j}(v_i) = \begin{cases} \dfrac{\rho(v_i, V_{0ji})}{\rho(v_i, V_{pi}) - \rho(v_i, V_{0ji})} & \rho(v_i, V_{pi}) - \rho(v_i, V_{0ji}) \neq 0 \\ -\rho(v_i, V_{0ji}) - 1 & \rho(v_i, V_{pi}) - \rho(v_i, V_{0ji}) = 0 \end{cases}. \tag{9}$$

Specifically,

$$\rho(v_i, V_{0ji}) = \left| v_i - \frac{a_{0ji} + b_{0ji}}{2} \right| - \frac{b_{0ji} - a_{0ji}}{2}, \tag{10}$$

$$\rho(v_i, V_{pi}) = \left| v_i - \frac{a_{pi} + b_{pi}}{2} \right| - \frac{b_{pi} - a_{pi}}{2}. \tag{11}$$

Calculation of the extent of correlation of evaluation matter element with rock burst grade

The extent of any correlation between the cavern section under evaluation (p) and rock burst grade (j) is expressed as:

$$K_{0j}(P) = \sum_{j=1}^{m} a_i K_{0j}(v_i), \tag{12}$$

where a_i is the weight coefficient of index c_i and $\sum_{i=1}^{n} a_i = 1$

Extensible evaluation grade

In the case of $K_{j\max}(P) = \max_{j \in \{1,2,3,\ldots,n\}} K_{0j}(p)$, it was deduced that p is in grade j.

Table 1 Rock burst evaluation indices and evaluation class

No.	R_c/MPa	R_c/σ_1	R_c/σ_t	W_{et}	σ_θ/R_c	H/m	K_V	Rock burst grade
1	(0, 80)	[14.5, $+\infty$)	[40, $+\infty$)	(0, 2)	(0, 0.3)	(0, 50)	(0, 0.55)	No rock burst/class 1
2	[80, 120)	[5.5, 14.5)	[26.7, 40)	[2, 3.5)	[0.3, 0.5)	[50, 200)	[0.55, 0.65)	Weak rock burst/class 2
3	[120, 180)	[2.5, 5.5)	[14.5, 26.7)	[3.5, 5)	[0.5, 0.7)	[200, 700)	[0.65, 0.75)	Medium rock burst/class 3
4	[180, $+\infty$)	(0, 2.5)	(0, 14.5)	[5, $+\infty$)	[0.7, $+\infty$)	[700, $+\infty$)	[0.75, 1]	Strong rock burst/class 4

Application of RS theory and extension theory

Selection of influencing factors and the construction of decision table

Previous studies have shown that the stress, lithology, and energy of the surrounding rock are the main factors affecting the rock burst grade. The stress of the surrounding rock can be described by the maximum tangential stress σ_θ of the cavern. The lithology can be described by the rock uniaxial compressive strength R_c and the tensile strength σ_t. The elastic energy index W_{et} is the ratio of the elastic strain energy accumulated before the peak strength of the elastic rock specimen to the lose energy obtained from the unloading. The greater the value, the more energy is released during the failure. Thus, W_{et} reflects the energy characteristics of the rock. The buried depth H of the tunnel reflects the magnitude of the geo-stress to a certain extent, and the K_V of the rock mass reflects the development degree of the fissure and joint.

This research takes the practical engineering project of the underground powerhouse caverns in Jiangbian hydropower station as an example. Based on the existing criteria for rock bursts and engineering cases in China and other countries, the following factors were selected as indices for evaluating occurrence of rock burst: uniaxial compressive strength (R_c), ratio of rock strength to in situ stress (R_c/σ_1), ratio of rock compressive strength to tensile strength (R_c/σ_1), t ratio of tangential stress and rock compressive strength (σ_θ/R_c), elastic strain energy index (W_{et}), depth of tunnel (H), and rock integrity (K_V). These parameters fully typify the characteristics of rock burst, and the parameters are relatively independent, which basically includes the internal and external conditions of the comprehensive rock burst, and can be obtained through indoor test or field test. Risk assessment levels of rock burst are divided into four levels: No rock burst (class 1), Weak rock burst (class 2), Medium rock burst (class 3), Strong rock burst (class 4), as shown in Table 1. According to many single factors, rock burst identification method and relevant literatures (Wang 1998; Chen et al. 2009; Shang et al. 2013; Zhang et al. 2014; Wang et al. 2014; Hao et al. 2016), the parameters of each index for evaluating rock bursts are listed in Table 1.

Selection of sample data

Rock mechanics tests were done in this site laboratory so that the mechanical parameters of the research sections in the caverns were obtained, such as the mean values of uniaxial compressive strength, tensile strength, and elastic energy index. Field terrestrial stress was measured by hollow inclusion stress gauge (Fig. 6), while the secondary stress field surrounding the rock samples was determined by numerical method (Zhang et al. 2012a, b). The rock-mass integrity index was determined from the wave velocities of rock masses, and rock blocks, which were obtained using an ultrasonic detecting instrument (Fig. 7). Twenty representative cavern sections with complete recorded data were chosen for further analysis: the parameters of the surrounding rock in these cavern sections were used as samples. Sample data are shown in Table 2.

Establishing the initial decision table

A condition attribute set was built based on interval division of the evaluation indices in Table 1 and chosen sample data. The initial decision table, with 20 rows and eight columns, was established by defining the real rock burst grades as the decision attribute set, as listed in Table 3.

Extraction of the major factors on the basis of RS theory

In this paper, these seven indicators are calculated by the rough set theory, resulting in nine groups of reduction (Table 4), each group classifying and evaluating rock burst, so we need to choose the most reasonable group from a professional point. Among these indexes, the depth of the cave reflects the magnitude of the stress value, the greater the depth is, and the greater the ground stress is. However, it is an empirical indicator so that it should be removed from the decision table. The ratio of rock

Fig. 6 Field terrestrial stress measured by hollow inclusion stress gauge

Fig. 7 Rock-mass integrity index determined by ultrasonic detecting instrument

compressive strength to tensile strength (R_c/σ_t) reflects the brittleness of the rock, indirectly reflects the energy storage capacity of the rock, and it has a very large correlation with elastic strain energy index (W_{et}) that is more able to reflect the energy storage capacity; therefore, it can also be removed from the decision table. The rock integrity (K_V) of the rock mass reflects the development degree of the fissure and joint. After comprehensive comparison, we found that the second reduced group is the best because there are no redundant factors in the selected indicators and the correlation between the factors is the smallest, and then the evaluation index system of rock burst is constructed.

Calculation of the weight of evaluation indices

According to Eq. (2), the degree of dependency of decision attribute set D in the decision table on all condition attributes in C was obtained ($\gamma_C(D) = 1.00$);

Based on Eqs. (2)–(5) and the discretised data in Table 3, weight coefficients of the factors influencing rock bursts were calculated, as shown in Table 5.

Table 2 Twenty representative cavern samples data

Sample	Location	R_c/MPa	R_c/σ_1	R_c/σ_t	W_{et}	σ_θ/R_c	H	K_V	Rock burst level
1	Construction branch tunnel	148.52	6.73	22.3	3.23	0.66	166	0.88	3
2	Traffic tunnel	162.33	2.91	13.2	5.23	0.72	317	0.71	4
3	Construction branch tunnel	116.78	5.12	29.73	3.52	0.37	177	0.68	2
4	Main powerhouse	109.33	11.36	32.77	2.97	0.42	148	0.71	2
5	Tailrace tunnel	98.56	15.23	42.73	2.17	0.28	171	0.49	1
6	Traffic tunnel	156.73	2.77	20.13	3.82	0.49	289	0.91	3
7	Main powerhouse	100.32	3.77	28.77	3.02	0.38	182	0.70	2
8	Traffic tunnel	142.20	3.63	27.52	4.30	0.72	308	0.73	3
9	High-pressure water diversion tunnel	160.32	2.37	16.55	5.72	0.69	265	0.90	4
10	Traffic tunnel	97.60	3.58	15.50	3.20	0.42	162	0.62	2
11	Main powerhouse	100.20	12.25	30.12	4.50	0.58	274	0.64	2
12	Construction branch tunnel	106.32	18.50	36.42	1.75	0.22	289	0.46	1
13	Traffic tunnel	125.77	4.85	10.36	5.75	0.65	277	0.92	3
14	Construction branch tunnel	146.75	10.05	19.35	4.50	0.62	318	0.88	3
15	Construction branch tunnel	107.75	5.30	31.20	3.15	0.57	276	0.58	2
16	Tailrace tunnel	160.75	2.06	12.36	5.41	0.65	294	0.91	4
17	Traffic tunnel	146.72	13.32	18.75	4.20	0.59	342	0.84	3
18	High-pressure water diversion tunnel	162.70	5.35	29.70	3.82	0.73	278	0.70	3
19	Construction branch tunnel	95.50	16.75	42.30	2.75	0.37	215	0.36	1
20	Tailrace tunnel	105.70	4.36	37.35	3.08	0.37	155	0.66	2

Table 3 Initial decision table established by defining the real rock burst grade

Sample	Location	R_c/MPa	R_c/σ_1	R_c/σ_t	W_{et}	σ_θ/R_c	H	K_V	Rock burst level
1	Construction branch tunnel	3	2	3	2	3	2	4	3
2	Traffic tunnel	3	3	4	4	4	3	3	4
3	Construction branch tunnel	2	3	2	3	2	3	3	2
4	Main powerhouse	2	2	2	2	2	2	3	2
5	Tailrace tunnel	2	1	1	2	1	2	1	1
6	Traffic tunnel	3	3	3	3	2	3	4	3
7	Main powerhouse	2	3	2	2	2	2	3	2
8	Traffic tunnel	3	3	2	3	4	3	3	3
9	High-pressure water diversion tunnel	3	4	3	4	3	3	4	4
10	Traffic tunnel	2	3	3	2	2	2	2	2
11	Main powerhouse	2	2	2	3	3	3	2	2
12	Construction branch tunnel	2	1	2	1	1	3	1	1
13	Traffic tunnel	3	3	4	4	3	3	4	3
14	Construction branch tunnel	3	2	3	3	3	3	4	3
15	Construction branch tunnel	2	3	2	2	3	3	2	2
16	Tailrace tunnel	3	4	3	4	3	3	4	4
17	Traffic tunnel	3	2	3	3	3	3	4	3
18	High-pressure water diversion tunnel	3	3	2	3	4	3	3	3
19	Construction branch tunnel	2	1	1	2	2	3	1	1
20	Tailrace tunnel	2	3	2	2	2	2	3	2

Table 4 Reduction results of initial decision table

No.	Reduction results
1	$\{C_1.C_2.C_3.C_7\}$
2	$\{C_1.C_2.C_4.C_7\}$
3	$\{C_1.C_3.C_4.C_7\}$
4	$\{C_1.C_2.C_3.C_5\}$
5	$\{C_2.C_3.C_5.C_6\}$
6	$\{C_2.C_3.C_5.C_7\}$
7	$\{C_1.C_2.C_4.C_5\}$
8	$\{C_2.C_4.C_5.C_7\}$
9	$\{C_3.C_4.C_5\}$

Application of extenics

The extension method is applied on the four tunnel sections (Fig. 3) in the study area on the basis of the four major influencing factors. Rock burst grade (ranging from no rock burst to slight, moderate, and strong types) is defined as I_1, I_2, I_3, and I_4, respectively, and $R_c, R_c/\sigma_1$, W_{et}, and K_V are denoted as C_1, C_2, C_3, and C_4 respectively. The classical matter element of each rock burst grade is established as follows by normalising the data in Table 1:

$$R_{01} = \begin{bmatrix} I_1 & C_1 & \langle 0.00, 0.33\rangle \\ & C_2 & \langle 0.73, 1.00\rangle \\ & C_3 & \langle 0.00, 0.25\rangle \\ & C_4 & \langle 0.00, 0.55\rangle \end{bmatrix}, \quad R_{02} = \begin{bmatrix} I_2 & C_1 & \langle 0.33, 0.50\rangle \\ & C_2 & \langle 0.28, 0.73\rangle \\ & C_3 & \langle 0.25, 0.44\rangle \\ & C_4 & \langle 0.55, 0.65\rangle \end{bmatrix}, \tag{13}$$

$$R_{03} = \begin{bmatrix} I_3 & C_1 & \langle 0.50, 0.75\rangle \\ & C_2 & \langle 0.13, 1.28\rangle \\ & C_3 & \langle 0.44, 0.63\rangle \\ & C_4 & \langle 0.65, 0.75\rangle \end{bmatrix}, \quad R_{04} = \begin{bmatrix} I_4 & C_1 & \langle 0.75, 1.00\rangle \\ & C_2 & \langle 0.00, 0.13\rangle \\ & C_3 & \langle 0.63, 1.00\rangle \\ & C_4 & \langle 0.75, 1.00\rangle \end{bmatrix}. \tag{14}$$

The matter element of the sectional field is expressed as:

$$R_p = \begin{bmatrix} P & C_1 & \langle 0.00, 1.00\rangle \\ & C_2 & \langle 0.00, 1.00\rangle \\ & C_3 & \langle 0.00, 1.00\rangle \\ & C_4 & \langle 0.00, 1.00\rangle \end{bmatrix}. \tag{15}$$

Index values of the four cavern sections under evaluation were calculated according to in situ and laboratory rock mechanics test and the data arising from geological site exploration, as shown in Table 6. According to Table 6, the matter elements of each cavern section under evaluation are:

Table 5 Support degrees, importance, and weight for each evaluation index

Evaluating indicator	R_c	R_c/σ_1	W_{et}	K_V
Index of dependence	0.85	0.85	0.85	0.9
The importance of indexes	0.15	0.15	0.15	0.10
Index weight coefficient	0.273	0.273	0.273	0.181

$$R_1 = \begin{bmatrix} P & C_1 & 0.33 \\ & C_2 & 0.56 \\ & C_3 & 0.87 \\ & C_4 & 0.55 \end{bmatrix}, \quad R_2 = \begin{bmatrix} P & C_1 & 0.34 \\ & C_2 & 0.51 \\ & C_3 & 0.85 \\ & C_4 & 0.48 \end{bmatrix}, \tag{16}$$

$$R_3 = \begin{bmatrix} P & C_1 & 0.37 \\ & C_2 & 0.64 \\ & C_3 & 0.88 \\ & C_4 & 0.65 \end{bmatrix}, \quad R_4 = \begin{bmatrix} P & C_1 & 0.46 \\ & C_2 & 0.79 \\ & C_3 & 0.89 \\ & C_4 & 0.63 \end{bmatrix}. \tag{17}$$

In accordance with the basic principles of extension theory, the correlation of each cavern section with each rock burst grade was obtained (Table 6). Evaluation results revealed that among the four cavern sections, the communication cavern and branch construction cavern suffered moderate rock bursts while the high-pressure branch pipe suffered a strong rock burst. The results were consistent with actual excavation conditions, thus revealing that the method in this research is feasible for rock burst prediction.

Discussion

The results of the proposed method were compared with that of fuzzy comprehensive (Wang et al. 1998), and efficacy coefficient methods (Wang et al. 2010). In the fuzzy comprehensive model, the weight was assigned according to expert opinions. In addition, fuzzy theory was introduced to address the imprecise index system. Then, a comprehensive evaluation vector was established by performing the fuzzy operation between the set of fuzzy weights and the fuzzy relationship matrix. On the other hand, in the efficacy coefficient model, the main content was to determine the value of the function coefficient based on quantitatively quantifying the multiple indexes, and then combine the function coefficient values to determine the comprehensive evaluation value, to evaluate the comprehensive situation of the object being studied. In short,

Table 6 Results of case study and comparison

Sample	Location	R_c	R_c/σ_1	W_{et}	K_V	Relational degree				Proposed level	Fuzzy comprehensive	Efficacy coefficient	Actual level
						K_{I}	K_{II}	K_{III}	K_{IV}				
1	Traffic tunnel	150.16	3.12	3.95	0.70	−0.4845	−0.2405	0.3646	−0.1965	III	III	III	III
2	Construction branch tunnel	142.56	6.10	3.52	0.76	−0.4317	−0.0916	0.0746	−0.2507	III	II	III	II–III
3	Construction branch tunnel	156.72	2.15	5.34	0.88	−0.6553	−0.4909	−0.0745	0.1135	IV	IV	III	III–IV
4	Construction branch tunnel	138.71	6.34	3.66	0.81	−0.4436	−0.1113	0.0389	−0.2118	III	III	III	III

the calculated results of the proposed method, fuzzy comprehensive method and efficacy coefficient method are listed in Table 6.

This paper considers seven rock burst factors (Table 3) because there is a certain correlation between the indicators, which will inevitably have a certain impact on the forecast results. At this time, we need to adopt a scientific and reasonable method to find the key indicators that affect the occurrence of rock burst and build the optimal evaluation index system. Under the premise of ensuring the correct decision classification of the rock burst prediction model, the attribute reduction operation in the rough set theory finds some condition attributes, which do not matter for the decision attribute from the decision table, and removes these conditional attributes from the decision table. In this way, we construct a decision table which is the simplest, and the relevance of the data in this table is the least, to establish a scientific and reasonable rock burst evaluation index system for engineering practical problems. In this paper, we use this method to analyze these seven influencing factors of rock burst and choose the four evaluation indexes, which has a large influence on the occurrence of rock burst, to establish the evaluation system.

Many factors influence the occurrence of rock burst. It is impossible to consider all the factors when constructing the rock burst evaluation index system. This requires a scientific method to construct a reasonable rock burst evaluation system. In the rough set theory, the attribute reduction operation can find and remove some condition attributes that are insignificant to the decision attribute from the decision table; therefore, we can construct a decision table with the simplest attribute set, to establish a scientific and reasonable rock burst evaluation index system for engineering practical problems. At the same time, in the rough set theory, the weight of the index is determined by the attribute importance evaluation method. The method does not need expert experience, and the result of weight calculation is completely determined by the actual sample data, which is an objective method to determine the weight of the index. Based on extensible set theory, from the qualitative and quantitative points extension evaluation method builds laws and methods in solving the contradiction, it reflects the comprehensive level of the contradiction through establishing an evaluation model relating to multiple index parameters (Cai 1997). Compared with the fuzzy mathematics and grey relational degree method, the extension evaluation transforms the evaluation index from the single definite value into the interval value, which is more suitable for practical application. Therefore, the combination of rough set theory and extension comprehensive evaluation method is more innovative and scientific than other methods, and has been successfully applied in many areas to solve practical problems (Zhang et al. 2009, 2013; Zhu et al. 2012).

Conclusions

This research proposed a method for predicting rock bursts in underground caverns based on rough set and extensible comprehensive evaluation. According to rough set theory, the factors influencing rock bursts in the underground powerhouse caverns of Jiangbian hydropower station, Sichuan, China, were investigated through attribute reduction, and the four main factors influencing rock burst occurrence and severity were obtained. Thereafter, by analysing the significance of condition attributes, the weight coefficients of each evaluation index were obtained. Finally, according to the basic principles of extension theory, a model for predicting rock bursts in the underground caverns of Jiangbian hydropower station was developed. The application of this method to an engineering case study proves that the method is feasible, operable, and provides guidance for future development and construction on the project at a later date.

Attribute reduction and the solution for the weights using rough set theory were based on real samples. Therefore, subjective influences were reduced to some extent, which led to more reasonable and reliable evaluation results. However, the accuracy of this method is influenced by the composition and number of samples. The more representative and numerous of the samples, the more reliable the calculated results are.

By introducing the concept of matter element into extension theory, each evaluation index was transformed into a compatible problem by establishing the model for each matter element. In this way, the rock burst grades are evaluated more comprehensively. This method presents high recognition accuracy for typical rock burst types. However, bursts incorporating facets of behaviour pertaining to two such types have to be determined by combining the judgment of engineering geologists in the field.

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