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ORIGINAL PAPER

A model for evaluation of surrounding rock stability based on D-S evidence theory and error-eliminating theory

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Abstract
In order to evaluate the stability of surrounding rock scientifically and reasonably, a model for evaluation of underground engineering surrounding rock stability based on D-S evidence theory and error-eliminating theory was proposed. Firstly, aiming at the fuzziness and complexity of index weight in the evaluation of surrounding rock stability, four groups of index weight were obtained by using four kinds of weighting methods and synthesized by D-S evidence theory to avoid the difference of single weighting method in calculating index weight. Then, 16 groups of measured rock mass data of the first-stage underground project in Guangzhou pumped storage power plant were taken as samples, and a model for the surrounding rock stability evaluation based on D-S evidence and error-eliminating was constructed. Finally, the established model was applied to the evaluation of the surrounding rock stability of the second-stage underground project of the power plant, and the evaluation results were consistent with those of the other four evaluation models. The results show that D-S evidence theory improves the weighting method, and error-eliminating theory optimizes the defect of setting upper and lower limit values in standard of surrounding rock evaluation. The evaluation results of the established model are accurate and reliable. It provides a new method for the evaluation of underground engineering surrounding rock stability and has certain guiding significance in engineering practice.

Keywords Safety system engineering · D-S evidence theory · Error-eliminating theory · The stability of surrounding rock · Multi-source weight

Introduction

The evaluation of surrounding rock stability is based on theoretical analysis and testing methods to judge the stability of surrounding rock. The grade of surrounding rock is a comprehensive reflection of the surrounding rock stability and an important basis for underground engineering design and construction. Also, the accuracy of classification is directly related to the economy and safety of the project. Because the evaluation of surrounding rock stability is complex system engineering, its classification index is fuzzy and uncertain (Gao et al. 2018; Wang and Guo 2019). Therefore, there are many methods to evaluate and classify the stability of surrounding rock, including on-site monitoring method (Han et al. 2017; Juang et al. 2016), numerical simulation (Li et al. 2016; Zhang et al. 2017; Zhu et al. 2020), and theoretical analysis (Gao et al. 2019; Peng et al. 2020; Zhang et al. 2020).

Site monitoring is the most traditional research method. It evaluates the stability of underground engineering surrounding rock based on site monitoring data. Martini et al. (1997) described in detail the excavation response and brittle failure process of deep buried hard rock circular tunnel. Read (2004) proposed measures to improve the stability of surrounding rock of deep caverns. Fang et al. (2016) collected and collated the vault settlement and horizontal convergence data of 103 mountain tunnels in China and systematically analyzed the relationship between surrounding rock deformation, stability time of surrounding rock deformation and surrounding rock grade, tunnel excavation area, and other factors.

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The numerical simulation is the main method to analyze the complex mechanical behavior of surrounding rock after excavation unloading. It mainly includes three types: continuum mechanics methods, such as Hillerborg et al. (1976) proposed a fracture mechanics model; discontinuous medium mechanics methods, such as Iwashita and Oda (2000) proposed a modified distinct element method; continuum and discontinuous medium combination methods, such as Lisjak et al. (2015) used this method to simulate the excavation of circular tunnels.

The theoretical analysis is to analyze the stress field and deformation field in the surrounding rock of the cavern by analytic method, including the method of surrounding rock stress evaluation, such as Hoek-Brown strength criterion (Saroglou and Bar 2020); the method of surrounding rock displacement evaluation, such as Yao et al. (2012) presented a hybrid method based on support vector machine to predict tunnel surrounding rock displacement; and the method of surrounding rock self-stability evaluation, such as the large deformation mechanism and supporting method (Chen et al. 2019b). In addition, many scholars pay attention to the classification of surrounding rock according to the surrounding rock stability evaluation index. Among them, the rock quality designation (*RQD*) (Zheng et al. 2018) is the most widely used classification method, and it is a single index classification method. Because the stability of surrounding rock is controlled by many factors, the study on the classification of surrounding rock stability has gradually changed from single factor to multi-factor comprehensive evaluation. Since 1970, many comprehensive classifications of rock mass have been proposed, such as Barton's Q-system classification (Naithani 2019) of rock mass quality index and iBeinwisk's geomechanics classification of jointed rock mass (RMR) (Kang et al. 2013). It should be noted that RMR method and Q-system are established on the basis of analysis of a large number of engineering cases around the world. These methods have universality and credibility, but their shortcomings are that there are too many indexes used, and the determination of quantitative index is subjective and arbitrary.

With the deepening of the research, many systematic theory methods have been introduced into the evaluation of rock quality (Chen et al. 2019a; Lin et al. 2018; Zhou et al. 2019) and surrounding rock stability (D'Obyrn and Hydzik-Wisniewska 2017; Tunsakul et al. 2018). Fattahi et al. (2015) used the fuzzy hierarchy process to evaluate the stability of surrounding rock in the excavation damage area. Wang et al. (2015) proposed a model of surrounding rock stability evaluation based on set pair analysis coupled with extenics. Rezaei et al. (2014) used the intelligent method based on fuzzy model to predict unconfined compressive strength of rock surrounding, which has theoretical guiding significance for the stability evaluation of surrounding rock. There are many other evaluation methods, including fuzzy mathematics-euthenics model (Zhang and Zhang 2018), ideal point combination weighting method (Wang et al. 2016), and uncertainty measure theory model (He et al. 2014). Its research trend reflects the classification of the surrounding rock stability that has gradually changed from single factor to multi-factor comprehensive evaluation. Although some achievements have been made in the study on the stability of surrounding rock, the following problems still exist:

(1) Index weight: There are many weighting methods, such as rough set, gray theory, entropy weight, and so on. The weights obtained by these weighting methods are quite different. It is not scientific and unreasonable to use some weighting methods alone, and the distribution coefficients of some combination weights have some problems such as too strong subjectivity and insufficient objective analysis.
(2) Sample data processing: When classifying the stability of surrounding rock with multi-index, most methods of surrounding rock stability evaluation need to use normalized formula to process the sample data and calculate the membership degree, and these methods need to set an upper and lower limit for the evaluation standards in order to obtain the maximum and minimum values. However, in engineering standards and specifications, some indexes have no upper and lower limits and only a critical value, which leads to the current method of data process unreasonable. Therefore, it is necessary to improve, perfect, or innovate the existing theory and model for the evaluation of surrounding rock stability.

Evidence theory was first proposed by Dempster in 1967 and further developed and improved by Shafer, so it is also called D-S evidence theory (Dempster et al. 1977). It is an inaccurate reasoning theory based on artificial intelligence. Riley (2015) effectively measures different types of uncertainty in simulation modeling by combining evidence theory and Bayesian theory. Rao and Annamdas (2013) developed a set of evidence modeling and analysis combination rules to effectively measure the uncertainty in engineering structures. Because of its flexibility, evidence theory can transform with probability theory, fuzzy set, and interval model (Jiang and Zhan 2017; Si et al. 2019) under certain conditions, so evidence theory is considered as a more general uncertainty analysis model. Thus, D-S evidence theory can be used to fuse the index weight obtained by various weighting methods to obtain scientific and comprehensive index weight.

Error-eliminating theory can process data according to a "right-wrong" criterion to avoid imposing upper and lower limits on the indexes in classification standards, which will lead to their disadvantage to engineering application. Since 1983, Guo and his scientific research team (Shi et al. 2010) have taken error as the starting point, integrated qualitative and quantitative methods on the basis of in-depth analysis and research on errors. Meanwhile, with the help of logic tools and mathematical tools, they have made preliminary research on the quantification, prediction, and elimination of errors. *An introduction to Error-Eliminating study* (Guo and Zhang 1995) studied the basic concepts and properties of general errors and establishes a quantitative description method for errors; *Theory, method and application of conflict and error in complex large-scale system* (Liu and Guo 2000) explained and quantificationally described the related concepts of error system, focusing on how to avoid and eliminate errors; and *Error system* (Guo 2012) discussed the rules to distinguish system errors.

This work take the measured data of surrounding rock of the first-stage underground project in Guangzhou pump accumulator electricity station as samples, a model for evaluation of surrounding rock stability based on D-S evidence theory and error-eliminating theory is constructed, and then the model is used to classify the surrounding rock stability of the second-stage underground project in Guangzhou pump accumulator electricity station and to test the reliability of the model.

D-S evidence theory

Basic concepts of D-S evidence theory

D-S evidence theory (Deng 2015; Zhao et al. 2020) is a mathematical method based on "evidence" and "combination" to deal with uncertain reasoning problems. It has a strong ability to deal with uncertain information and meets weaker conditions than Bayesian probability theory (Chen et al. 2016).

For a recognition framework Θ, the basic probability assignment on Θ is a function m of $2^{\Theta} \rightarrow [0, 1]$ and satisfies the requirement as follows:

$$m(\varnothing) = 0 \text{ and } \sum_{A \subseteq \Theta} m(A) = 1 \tag{1}$$

where A that makes $m(A) > 0$ is called focal element.

The trust function based on the basic probability assignment function m is defined as:

$$Bel(A) = \sum_{B \subseteq A} m(B) \tag{2}$$

$Bel(A)$ indicates the degree of true for A.

The likelihood function based on the basic probability assignment function m is defined as:

$$Pl(A) = \sum_{B \cap A \neq \varnothing} m(B) \tag{3}$$

$Pl(A)$ indicates the degree of not false for A.

Since $Pl(A) \geq Bel(A)$, $Bel(A)$ and $Pl(A)$ are the lower and upper limits of degree of true for A, respectively. A hypothesis

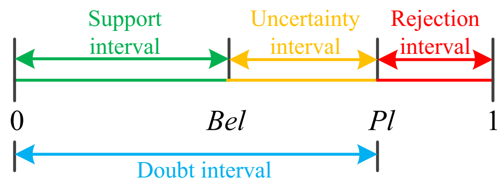

Fig. 1 Uncertainty representation of information

A in recognition framework Θ is confirmed by trust intervals $[Bel(A), Pl(A)]$. $Pl(A) - Bel(A)$ indicates the degree of uncertainty about a, and Fig. 1 shows the uncertainty of information in D-S evidence theory.

Rules of evidence composition

Suppose that the two evidences acting on the recognition framework Θ are E_1 and E_2 respectively, the corresponding trust functions are m_1 and m_2, and the focal element is A_i, as shown in Fig. 2.

A series of rectangles as shown in Fig. 3 can be obtained by combining the two evidences E_1 and E_2. The rectangle can be regarded as a new basic probability assignment obtained by the joint action of the two evidences.

Let $\forall A \subseteq \Theta$, two basic probability assignment functions m_1 and m_2 on Θ have evidence synthesis rules as follows:

$$m_1 \oplus m_2(A) = \frac{1}{K} \sum_{B \cap C = A} m_1(B) \cdot m_2(C) \tag{4}$$

where K is the normalized constant.

$$K = \sum_{B \cap C \neq \varnothing} m_1(B) \cdot m_2(C) = 1 - \sum_{B \cap C = \varnothing} m_1(B) \cdot m_2(C) \tag{5}$$

For $\forall A \subseteq \Theta$, multiple basic probability assignment functions $m_1, m_2, \ldots, m_n$ on Θ, the rules of evidence synthesis are as follows:

$$(m_1 \oplus m_2 \oplus \ldots \oplus m_n)(A) = \frac{1}{K} \sum_{A_1 \cap A_2 \cap \ldots \cap A_n = A} m_1(A_1) \cdot m_2(A_2) \ldots m_n(A_n) \tag{6}$$

$$K = \sum_{A_1 \cap A_2 \cap \ldots \cap A_n \neq \varnothing} m_1(A_1) \cdot m_2(A_2) \ldots m_n(A_n) = 1 - \sum_{A_1 \cap A_2 \cap \ldots \cap A_n = \varnothing} m_1(A_1) \cdot m_2(A_2) \ldots m_n(A_n) \tag{7}$$

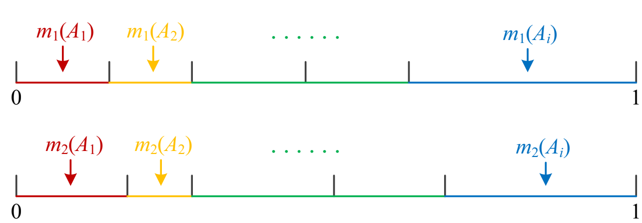

Fig. 2 Basic probability assignment on each focal element of evidence E_1 and E_2

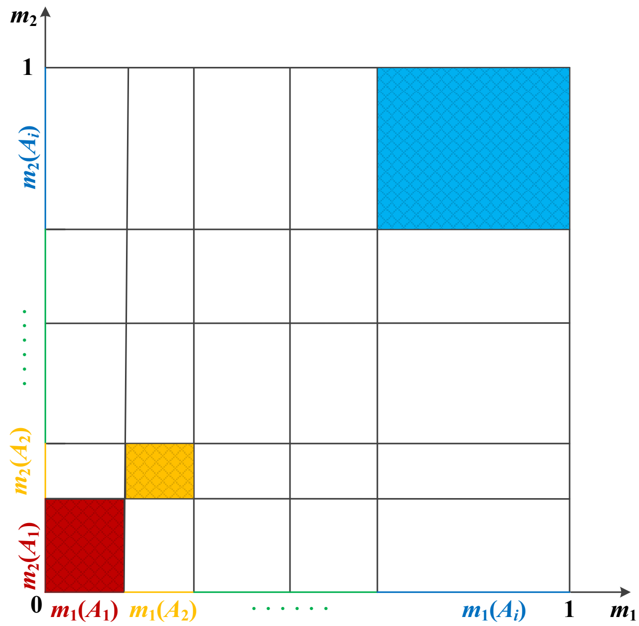

Fig. 3 Schematic diagram of evidence synthesis rules

Error-eliminating theory and its improvement

Error-eliminating theory

Error-eliminating (Huang and Cai 2016) is a theoretical method to study the mechanism, transmission, and transformation of errors and then to predict, reduce, and eliminate errors. Its basic error analysis structure is shown in Fig. 4.

For a universe U, $a \in U$, G is the right-wrong identification rule of U. If U cannot infer a, then a is wrong for G on U.

Let $V = \{(u, G) | u \in U\}$, f: $V \rightarrow R$, f is an error function defined on U for G; and $x = f(G,u)$, abbreviated as $f(u)$. R is the real field and x is the error value of object u based on G.

In error-eliminating theory, data normalization processing uses error function. For the evaluation object S_i, the error function of benefit index is as follows:

$$f(G,u) = \begin{cases} e^{1/(z-t)} & z < t \\ 0 & z = t \\ -e^{1/(t-z)} & z > t \end{cases} \tag{8}$$

The error function of cost-based index is as follows:

$$f(G,u) = \begin{cases} -e^{1/(z-t)} & z < t \\ 0 & z = t \\ e^{1/(t-z)} & z > t \end{cases} \tag{9}$$

where z is the index value and t is the target value.

Improvement of error function

The dimension of indexes of surrounding rock stability evaluation is different, which makes the index data quite different. The index value of analysis is not the same dimension, which makes the analysis difficult, and affects the accuracy of modeling. In order to eliminate this disadvantage, z-score (Cheadle et al. 2003) is used to transform the index data into score without unit, which makes the data standard unified and improves the data comparability. The calculation formula of z-score standardization is as follows:

$$z' = \frac{z-\mu}{\delta} \tag{10}$$

z' standardized index value
μ index mean value
δ index variance

Correspondingly, the target value t of the index is transferred to t' by standardization.

The improved error functions of benefit index and cost-based index are as follows:

$$f(G,u) = \begin{cases} e^{1/(z'-t')} & z' < t' \\ 0 & z' = t' \\ -e^{1/(t'-z')} & z' > t' \end{cases} \tag{11}$$

$$f(G,u) = \begin{cases} -e^{1/(z'-t')} & z' < t' \\ 0 & z' = t' \\ e^{1/(t'-z')} & z' > t' \end{cases} \tag{12}$$

Systematic comprehensive evaluation based on error-eliminating theory

The error matrix $\boldsymbol{X}$ of the evaluation object system is composed of m evaluated objects and n elements.

$$X = \begin{bmatrix} x_{11}\ x_{12} \cdots x_{1n} \\ x_{21}\ x_{22} \cdots x_{2n} \\ \vdots \quad \vdots \quad \vdots \\ x_{m1}\ x_{m2} \cdots x_{mn} \end{bmatrix} \tag{13}$$

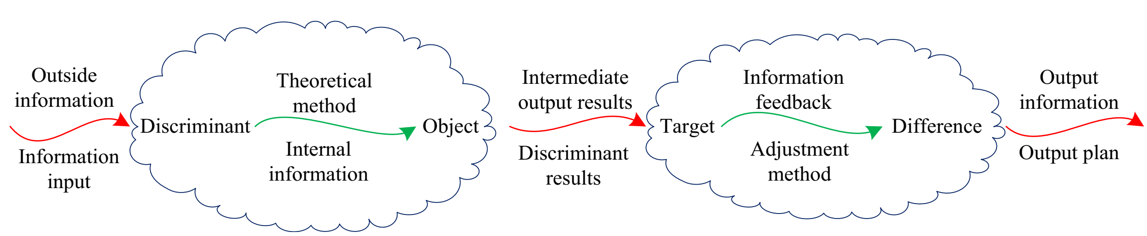

Fig. 4 Basic structure of error analysis

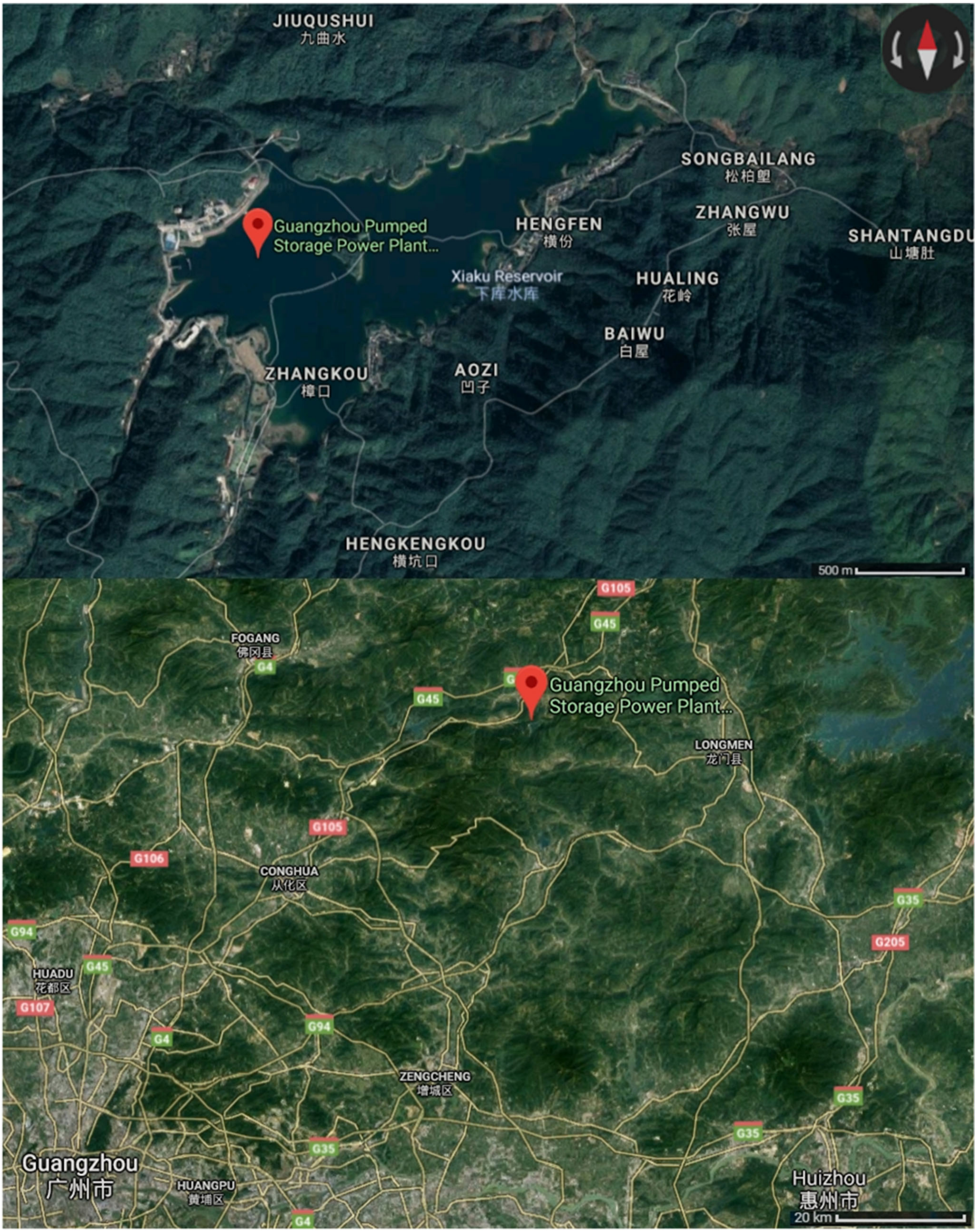

Fig. 5 Geographical location map of Guangzhou pumped storage power plant

Table 1 The data of surrounding rock of the first-stage project in Guangzhou pumped storage power plant

Sample	RQD (%)	R_W (MPa)	K_v	K_f	W/ [L ·(min ·10 m)$^{-1}$]	Surrounding rock grade
1	71.8	90.1	0.57	0.45	0	II
2	51	40.2	0.38	0.55	10.5	III
3	52	25	0.22	0.52	12	III
4	68	90	0.38	0.38	21	III
5	28	40	0.32	0.3	18.5	IV
6	51	45	0.15	0.3	5	III
7	76	95	0.7	0.55	12	II
8	87	95	0.7	0.5	9.8	II
9	76	90	0.57	0.5	11	II
10	50	35	0.32	0.35	20	III
11	68	90	0.57	0.35	18.5	III
12	82	95	0.7	0.35	0	II
13	52.5	28.6	0.38	0.16	23	IV
14	75	87.3	0.3	0.63	0	II
15	52.5	70.5	0.6	0.4	15	III
16	78	130.5	0.75	0.5	10	II

Assuming that the intrinsic function of a system is GY_i, when the object S_i makes a complete error on the index y_i, the reduction value h_i of S_i on the intrinsic function GY_i is the limit loss value of S_i on the index y_i.

The limit loss vector of n indexes is $H = [h_1\ h_2 \ldots h_n]$.

According to the limit loss vector H and error matrix X, the comprehensive evaluation vector L is as follows:

$$L = H{\cdot}X^T = [B_1\ B_2 \cdots B_m] \tag{14}$$

B_i is weighted error value. By comparing the comprehensive evaluation vector L of the object with the criterion of "right-wrong," the comprehensive evaluation of the object is obtained.

The model of surrounding rock stability evaluation based on D-S evidence theory and error-eliminating theory

Engineering overview

In this paper, the first-stage underground project in Guangzhou pumped storage power plant is selected as an engineering case for modeling. Guangzhou pumped storage power plant is located in the deep valley of Lutian Town, Conghua District, Guangzhou City, on the north side of the Nankun Mountains. It is 100 km away from Guangzhou and covers an area of 27 km^2. It is the second largest installed capacity pumped storage power plant in the world. It belongs to the supporting project of Daya Bay Nuclear Power Station. It is built to ensure the safe and economic operation of Daya Bay Power Station and meet the needs of filling valleys and peak shaving in Guangdong Power Grid. It is China's industrial tourism demonstration site, high-tech tourism scenic spot. The power station is divided into two stages. The first stage of the project was completed in March 1994, and the second stage started operation in December 1998 and put into operation in 2000. Its geographical location is shown in Fig. 5.

The surrounding rock of underground engineering in this project area is mainly fresh-slightly weathered granite. Because of geological process, the granite in this area forms alteration zones such as montmorillonite, hydrodolomitization, kaolinization, chloritization, and carbonation. In particular, montmorillonite is the most serious. However, because the alteration zone is formed from the bottom to the top and from the inside to the

Table 2 Standard of surrounding rock stability evaluation

Grades	RQD (%)	R_W (MPa)	K_v	K_f	W/ [L· (min ·10 m)$^{-1}$]
I (stability)	> 90	> 120	> 0.75	> 0.8	< 5
II (basic stability)	75~90	60~120	0.45~0.75	0.6~0.8	5~10
III (poor stability)	50~75	30~60	0.3~0.45	0.4~0.6	10~25
IV (instability)	25~50	15~30	0.2~0.3	0.2~0.4	25~125
V (extremely instability)	< 25	< 15	< 0.2	< 0.2	> 125

Table 3 Data standardization

Sample	Standardized data by *z*-score				
	RQD	R_W	K_v	K_f	*W*
I	1.4883	1.5102	1.4541	2.3714	−0.4763
II	0.6633	−0.2530	−0.0792	1.0558	−0.2867
III	−0.7117	−1.1346	−0.8459	−0.2598	0.2818
IV	−2.0867	−1.5754	−1.3570	−1.5754	4.0723
1	0.4873	0.6315	0.5341	0.0691	−0.6658
2	−0.6567	−0.8349	−0.4370	0.7269	−0.2678
3	−0.6017	−1.2815	−1.2548	0.5295	−0.2109
4	0.2783	0.6286	−0.4370	−0.3914	0.1302
5	−1.9217	−0.8407	−0.7437	−0.9176	0.0354
6	−0.6567	−0.6938	−1.6126	−0.9176	−0.4763
7	0.7183	0.7755	1.1986	0.7269	−0.2109
8	1.3233	0.7755	1.1986	0.3980	−0.2943
9	0.7183	0.6286	0.5341	0.3980	−0.2488
10	−0.7117	−0.9877	−0.7437	−0.5887	0.0923
11	0.2783	0.6286	0.5341	−0.5887	0.0354
12	1.0483	0.7755	1.1986	−0.5887	−0.6658
13	−0.5742	−1.1757	−0.4370	−1.8386	0.2060
14	0.6633	0.5492	−0.8459	1.2531	−0.6658
15	−0.5742	0.0555	0.6875	−0.2598	−0.0972
16	0.8283	1.8187	1.4541	0.3980	−0.2867

outside, it still has considerable strength in the closed state, so the timely closure after excavation will maintain the stability of surrounding rock. The in situ stress is the superposition of gravity stress field and tectonic stress field, and the gravity stress is the main one. The stability of the project is mainly controlled by the granite argillization alteration zone, and there is groundwater outcrop between the cavern fracture zones. According to the actual situation of the project (Cai 2001), considering the correlation between the indexes and the difficulty of obtaining the index data, rock quality designation (*RQD*), saturated uniaxial compressive rock strength (R_W), rock-mass integrity index (K_v), coefficient of weathering (K_f), and groundwater seepage (*W*) are selected as the indexes of the evaluation of surrounding rock stability. *RQD* refers to the ratio of cumulative core length equal to or greater than 10 cm and total drilling length in footage, R_W is the compressive strength when the sample reaches saturated water content, K_v is the square of the ratio of rock mass P-wave velocity to rock P-wave velocity, K_f is the ratio of uniaxial saturated compressive strength of weathered rock to fresh rock, and *W* is the monitored underground tunnel water flow.

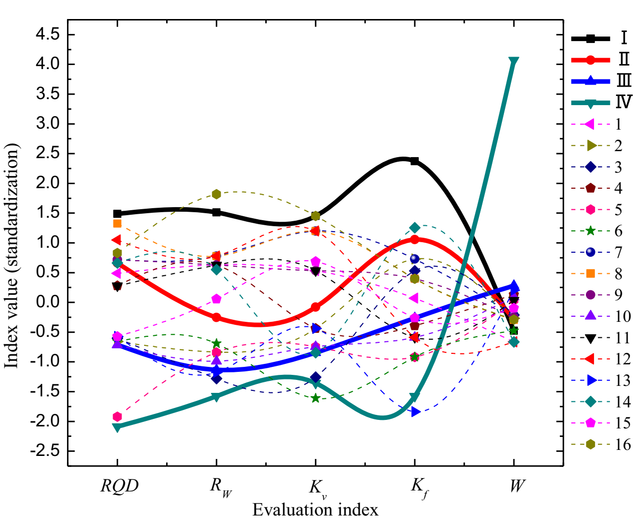

Fig. 6 Data distribution of evaluation index

Sixteen groups of measured rock mass data of the first-stage underground project in Guangzhou pumped storage power plant are shown in Table 1.

According to *Specification for design of hydraulic tunnel* and the classification standards provided by the project (Cai 2001), the stability of surrounding rock is divided into five grades. The specific date is shown in Table 2.

Compared with the standard of other evaluation models, the index values do not set the upper and lower limits, which ensure the rationality of index value in the evaluation standards.

Data standardization

According to Table 2, 16 groups of index value distribution of samples are analyzed. Sample data and the boundary point data of adjacent grades in the standard are standardized by *z-score*. The standardized data are shown in Table 3 and the data distribution is shown in Fig. 6.

From Fig. 6, it can be seen that the index values of samples vary greatly and distribute widely, and there is no regularity among the evaluation index values of each sample. The grade of each evaluation index value of a single sample is inconsistent, and the surrounding rock stability of the samples cannot be judged directly according to a single index. Therefore, these samples can be used to test the accuracy of the prediction results of the model.

Index weight based on D-S evidence theory

Index weight is one of the key problems in the evaluation of surrounding rock stability. Owing to the fuzziness and uncertainty of weights, there are great differences among various weighting methods, and the contradiction between indexes cannot be solved by using a single weighting method. In order to express the index weight more comprehensively and scientifically, firstly, we use subjective and objective weighting

Table 4 Evidence composition of index weights

Weight method	Evidence	RQD (%)	R_W (MPa)	K_v	K_f	W/ [L ·(min· 10 m)$^{-1}$]
RS	m_1	0.2000	0.2000	0.1333	0.2000	0.2667
Gray theory	m_2	0.2000	0.2000	0.2000	0.2000	0.2000
EWM	m_3	0.2000	0.2236	0.2797	0.2031	0.0935
AHP	m_4	0.2200	0.2000	0.1800	0.2200	0.1800
	m_{12}	0.2000	0.2000	0.1333	0.2000	0.2667
	m_{123}	0.2133	0.2384	0.1987	0.2165	0.1329
	m_{1234}	0.2303	0.2340	0.1756	0.2339	0.1174

methods to calculate the index weight, including analytic hierarchy process (AHP) (Shi et al. 2014), rough set (RS) (Hu et al. 2012), gray theory (Chen et al. 2018), and entropy weight method (EWM) (Zhou and Li 2012), and get 4 groups of index weight. Secondly, 4 groups of weights are synthesized by using D-S evidence theory in the field of artificial intelligence. Through uncertain and inaccurate reasoning, the index weight of information science and comprehensiveness is obtained. The composite data of weights are shown in Table 4 and Fig. 7.

From Table 4 and Fig. 7, it can be seen that the index weight obtained by the 4 weighting methods is quite different, and it is difficult to compare the results of different weighting methods. In order to fuse the information contained in different empowerment methods, 4 groups of weights are synthesized by using D-S evidence theory. The weight vector of indexes based on D-S evidence theory is as follows:

V = [0.2303 0.2340 0.1756 0.2339 0.1174].

Through the analysis of multi-source evidence weight fusion in Fig. 7, there is no obvious correlation between the weights, which is the result of weight synthesis based on artificial intelligence. The m_1 is the same as m_{12} because the values in m_2 are the same. According to D-S evidence theory, 4 groups of original weights are independent sources of evidence. Evidence synthesis rules can obtain new weights that integrate evidential information.

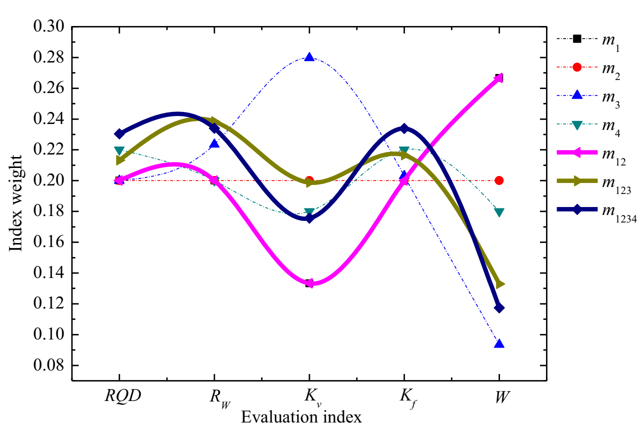

Fig. 7 Weight change of multi-source evidence

Evaluation of surrounding rock stability based on error-eliminating theory

In order to obtain the classification range of surrounding rock stability at all grades, the data of standard are included in the samples. Because of the different dimensions of evaluation indexes, z-score is used to standardize the sample data. According to the idea of error-eliminating theory, when using error-eliminating function to process data, it is necessary to determine a "right-wrong" discriminate rule, in which the stability of grade I surrounding rock is taken as the "right-wrong" discriminate rule, i.e., the grade I standard of 5 indexes [90 120 0.75 0.8 5] is taken as the objective value. Equations (11) and (12) are used to calculate the error values of sample data and get the error matrix. Rock quality designation (RQD), saturated uniaxial compressive rock strength (R_W), rock-mass integrity index (K_v), and intensity of structure coefficient (K_f) are benefit indexes, and groundwater seepage (W) is cost index.

According to the definition of the limit loss vector of the index, the normalized limit loss vector of the index is the index weight vector.

The weighted error values of each sample are obtained by multiplying the limit loss vector of the index and the error matrix. The results are shown in Table 5 and Fig. 8.

From the weighted error value B in Table 5, the classification range of surrounding rock stability can be obtained as follows:

Grade I: $B < 0.0000$
Grade II: $0.0000 \le B \le 0.4027$
Grade III: $0.4027 \le B \le 0.6116$
Grade IV: $0.6116 \le B \le 0.7422$
Grade V: $B > 0.7422$

From the numerical range of all grades, it can be seen that the weighted error value of grade I is 0. The worse the stability of surrounding rock is, the greater the weighted error value is. Through the classification range of weighted error values of surrounding rock stability and the weighted error values of samples, the grade of surrounding rock stability of samples

Table 5 The results of the model for the surrounding rock stability evaluation based on D-S evidence and error-eliminating

Sample	Error value					Weighted error value (B)	Actual	This work
	RQD (%)	R_W (MPa)	K_v	K_f	W/[L ·(min ·10 m)$^{-1}$]			
I	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	I	I
II	0.2976	0.5671	0.5209	0.4676	0.0051	0.4027	II	II
III	0.6347	0.6852	0.6474	0.6838	0.2674	0.6116	III	III
IV	0.7560	0.7232	0.7007	0.7762	0.8026	0.7422	IV	IV
1	0.3682	0.3204	0.3372	0.6477	−0.0051	0.3699	II	II
2	0.6274	0.6528	0.5893	0.5444	0.0083	0.5291	III	III
3	0.6197	0.6989	0.6913	0.5810	0.0231	0.5663	III	III
4	0.4376	0.3217	0.5893	0.6963	0.1923	0.4650	III	III
5	0.7458	0.6535	0.6344	0.7378	0.1417	0.6253	IV	IV
6	0.6274	0.6353	0.7217	0.7378	0.0000	0.5925	III	III
7	0.2729	0.2564	0.0200	0.5444	0.0231	0.2564	II	II
8	0.0023	0.2564	0.0200	0.6025	0.0041	0.2054	II	II
9	0.2729	0.3217	0.3372	0.6025	0.0123	0.3397	II	II
10	0.6347	0.6701	0.6344	0.7133	0.1723	0.6015	III	III
11	0.4376	0.3217	0.3372	0.7133	0.1417	0.4187	III	III
12	0.1030	0.2564	0.0200	0.7133	−0.0051	0.2535	II	II
13	0.6158	0.6891	0.5893	0.7886	0.2309	0.6181	IV	IV
14	0.2976	0.3532	0.6474	0.4089	−0.0051	0.3599	II	II
15	0.6158	0.5029	0.2713	0.6838	0.0715	0.4755	III	III
16	0.2198	−0.0391	0.0000	0.6025	0.0051	0.1830	II	II

can be obtained. From the evaluation results, it can be seen that the evaluation results of 16 group samples are consistent with the actual situation.

Application and analysis

According to the engineering data, the second-stage project is not far from the first-stage project, and the geological conditions are similar. In order to verify the reliability of the established model, the established model is used to evaluate the stability of surrounding rock of the second-stage project,

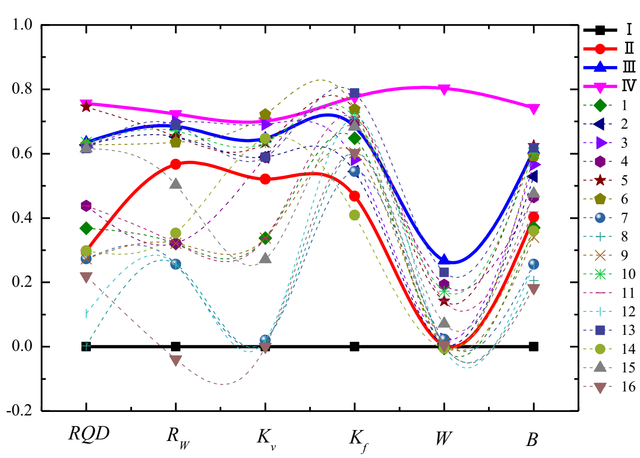

Fig. 8 Classification range of surrounding rock stability

and the evaluation results are compared with those of RS-TOPSIS (Hu et al. 2012), CL-FO (Wu et al. 2015), ANN (Cai 2001), and SVM (Lai 2004). The comparison results are shown in Table 6.

According to the standard of surrounding rock stability evaluation in Table 2, the grade of each index of samples in Table 6 is determined, as shown in Fig. 9.

As can be seen from Fig. 9, due to the different grades of the indexes in the samples, their grades are irregularly distributed between I and V, so it is impossible to directly evaluate these samples. Thus, the evaluation of these samples has practical significance for safe construction.

From Table 6, it can be seen that the evaluation results of samples include II, III, and VI, which ensures the diversity of samples. The evaluation results of the five models of surrounding rock stability are consistent, which shows that the model based on D-S evidence and error-eliminating is reliable. Compared with other models for surrounding rock stability evaluation, the constructed model can fuse the weights obtained by different weighting methods to improve the objectivity of the weight determination process. When dealing with index value of the surrounding rock stability evaluation, the upper and lower limits of the index value need not be set for the single index evaluation standards and the data processing is more reasonable. The established model for

Table 6 Comparisons of results of surrounding rock stability evaluation of the second project

No.	Footage (m)	Weathering corrosion	RQD (%)	R_W (MPa)	K_v	K_f	W/[L ·(min ·10 m)$^{-1}$]	Evaluation results				
								This work	RS-TOPSIS	CL-FO	ANN	SVM
1	0 + 000~0 + 067	Fault alteration zone of medium to weak weathering	26	36	0.22	0.35	5	IV	IV	IV	IV	IV
2			50	40.2	0.5	0.5	10	III	III	III	III	III
3	0 + 067~0 + 130	Weak weathered	52	25	0.2	0.5	5	III	III	III	III	III
4			71	90	0.35	0.3	18	III	III	III	III	III
5	0 + 130~0 + 198	Slightly weathered	75	95	0.7	0.5	0	II	II	II	II	II
6			77.5	90	0.57	0.45	10	II	II	II	II	II
7	0 + 198~0 + 297	Fault alteration zone	50	70	0.5	0.25	5	III	III	III	III	III
8			50.9	34	0.32	0.35	21	III	III	III	III	III

the evaluation of surrounding rock stability based on D-S evidence and error-eliminating has wider applicability than other models.

Conclusions

The factors affecting the stability of surrounding rock of underground engineering are complex and have strong fuzziness and uncertainty. On the basis of selecting the main indexes affecting the stability of surrounding rock, the D-S evidence theory is introduced to fuse the multi-source weights of the indexes. In view of the shortcomings of normalization of the index values, the error-eliminating is used to deal with the values of the surrounding rock stability evaluation indexes, which provides a theoretical basis for rational evaluation and analysis of the surrounding rock stability.

(1) The method for determining the index weight of surrounding rock stability evaluation is improved. The method of multiple weight fusion based on evidence theory solves the problem that it is difficult to choose the weighting method. As many indexes involved in the evaluation of surrounding rock stability, and influence degree of each index on the classification of surrounding rock stability is fuzzy, the weight information is fused based on D-S evidence theory. According to the rules of evidence synthesis, the index weights obtained by different weighting methods are synthesized to avoid the differences in the expression of the importance of indexes by different weighting methods.

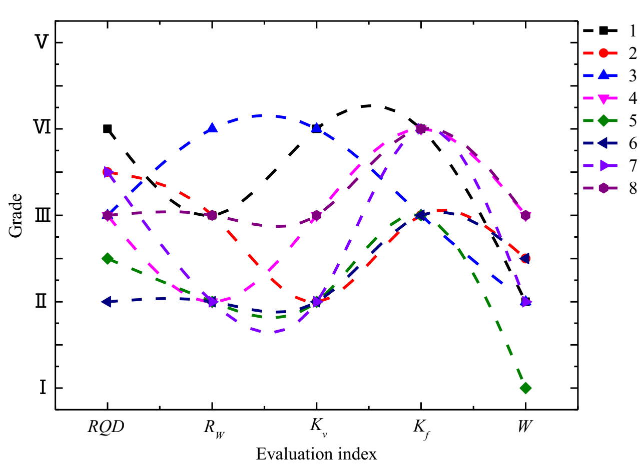

Fig. 9 Grade distribution of sample indexes in second-stage project

(2) The shortcomings of normalizing the index values by setting upper and lower limits in the evaluation standard are optimized. Most models for the evaluation of surrounding rock stability need to set the upper and lower limits of the index values in the standard because they use normalized function to process the index dimensionless. Error function takes a certain grade in the standard of surrounding rock stability evaluation as the criterion of “right-wrong” and then calculates the error value of samples. It avoids the irrationality and limitation of data processing of normalized function and is more conducive to engineering application.

(3) The model based on D-S evidence theory and error-eliminating theory is established and applied to engineering. According to the modeling method of error-eliminating theory, the stability of grade I surrounding rock is taken as the target value and error function is used to calculate the error value of samples. Meanwhile, the index weight based on D-S evidence theory is taken as the normalized limit loss value of index. The proposed model is applied to the surrounding rock samples of the first-stage underground project in Guangzhou pumped storage power plant, and the evaluation results are consistent with the actual stability of surrounding rock. Simultaneously, the established model is applied to the evaluation of surrounding rock stability of the second-

stage project, and the evaluation results are consistent with those of other four evaluation models, which show that the established model based on D-S evidence theory and error-eliminating theory is reliable.

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Data availability The data used to support the findings of this study are included within the article.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

References

Cai G (2001) Study of the BP neural network on the stability classification of surrounding rocks. Hohai University, Jiangsu, China

Cheadle C, Cho-Chung YS, Becker KG, Vawter MP (2003) Application of z-score transformation to Affymetrix data. Appl Bioinforma 2(4): 209–217

Chen H, Liu W, Wang L (2016) Naive Bayesian classification of uncertain objects based on the theory of interval probability. Int J Artif Intell Tools 25(3):1650012

Chen S, Wu A, Wang Y, Chen X (2018) Multi-objective optimization of stope structure parameters in broken rock conditions using grey relational analysis. Arch Min Sci 63(2):269–282

Chen J, Zhao Y, Shan Y (2019a) Research on the classification of slope stability state based on the method of vectorization attribute circle. IEEE Access 7:74879–74889

Chen Z, He C, Xu G, Ma G, Yang W (2019b) Supporting mechanism and mechanical behavior of a double primary support method for tunnels in broken phyllite under high geo-stress: a case study. Bull Eng Geol Environ 78(7):5253–5267

Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood from incomplete data via the EM algorithm. J R Stat Soc 1(39):1–38

Deng Y (2015) Generalized evidence theory. Appl Intell 43(3):530–543

D'Obyrn K, Hydzik-Wisniewska J (2017) Assessment of rock mass stability in the historic area of levels VI-V of the “Wieliczka” Salt Mine. Arch Min Sci 62(1):189–202

Fang Q, Su W, Zhang D, Yu F (2016) Tunnel deformation characteristics based on on-site monitoring data. Chin J Rock Mech Eng 35(9): 1884–1897

Fattahi H, Farsangi MAE, Shojaee S, Mansouri H (2015) Selection of a suitable method for the assessment of excavation damage zone using fuzzy AHP in Aba Saleh Almahdi tunnel, Iran. Arab J Geosci 8(5): 2863–2877

Gao W, Chen D, Dai S, Wang X (2018) Back analysis for mechanical parameters of surrounding rock for underground roadways based on new neural network. Eng Comput 34(1):25–36

Gao C, Huang D, Chang X, Xi H (2019) Risk analysis and extension assessment for the stability of surrounding rock in deep coal roadway. Int J Environ Res Public Health 16(23):4752

Guo K (2012) Error system. Science Press, Beijing

Guo K, Zhang S (1995) An introduction to error-eliminating study. South China University of Technology Press, Guangzhou

Han X, Yang S, Zhou F, Wang J, Zhou D (2017) An effective approach for rock mass discontinuity extraction based on terrestrial LiDAR scanning 3d point clouds. IEEE Access 5:26734–26742

He H, Yan Y, Qu C, Fan Y (2014) Study and application on stability classification of tunnel surrounding rock based on uncertainty measure theory. Math Probl Eng 2014(12):1–5

Hillerborg A, Modéer M, Petersson PE (1976) Analysis of crack formation and crack growth in concrete by means of fracture mechanics and finite elements. Cem Concr Res 6(6):773–781

Hu J, Shang J, Lei T (2012) Rock mass quality evaluation of underground engineering based on RS-TOPSIS method. J Cent South Univ 43(11):4412–4419

Huang H, Cai K (2016) A method of fuzzy multiple attribute decision making based on the error-eliminating theory. J Intell Fuzzy Syst 31(4):2119–2127

Iwashita K, Oda M (2000) Micro-deformation mechanism of shear banding process based on modified distinct element method. Powder Technol 109(1–3):192–205

Jiang W, Zhan J (2017) A modified combination rule in generalized evidence theory. Appl Intell 46(3):630–640

Juang CH, Carranza-Torres C, Crosta G, Dong J, Gokceoglu C, Jibson RW, Shakoor A, Tang H, van Asch TWJ, Wasowski J (2016) Engineering geology—a fifty year perspective. Eng Geol 201:67–70

Kang S, Kim H, Jang B (2013) Correlation of in situ modulus of deformation with degree of weathering, RMR and Q-system. Environ Earth Sci 69(8):2671–2678

Lai Y (2004) Application and study of support vector machine in the underground engineering. Shandong University of Science and Technology, Qingdao, China

Li X, Wang S, Malekian R, Hao S, Li Z (2016) Numerical simulation of rock breakage modes under confining pressures in deep mining: an experimental investigation. IEEE Access 4:5710–5720

Lin Y, Zhou K, Li J (2018) Application of cloud model in rock burst prediction and performance comparison with three machine learnings algorithms. IEEE Access 6:30958–30968

Lisjak A, Garitte B, Grasselli G, Mueller HR, Vietor T (2015) The excavation of a circular tunnel in a bedded argillaceous rock (Opalinus Clay): short-term rock mass response and FDEM numerical analysis. Tunn Undergr Space Technol 45:227–248

Liu Y, Guo K (2000) Theory, method and application of conflict and error in complex large-scale system. South China University of Technology Press, Guangzhou

Martini CD, Read RS, Martino JB (1997) Observations of brittle failure around a circular test tunnel. Int J Rock Mech Min Sci 34(7):1065–1073

Naithani AK (2019) Rock mass classification and support design using the Q-system. J Geol Soc India 94(4):443

Peng Y, Wu L, Chen C, Yue J (2020) Stability analysis of surrounding rock in tunnel crossing water-rich fault based on catastrophe theory. Geotech Geol Eng 38(1):415–423

Rao S, Annamdas K (2013) A comparative study of evidence theories in the modeling, analysis, and design of engineering systems. J Mech Des 6(135):061006

Read RS (2004) 20 years of excavation response studies at AECL’s underground research laboratory. Int J Rock Mech Min Sci 41(8): 1251–1275

Rezaei M, Majdi A, Monjezi M (2014) An intelligent approach to predict unconfined compressive strength of rock surrounding access tunnels in longwall coal mining. Neural Comput Applic 24(1SI):233–241

Riley ME (2015) Evidence-based quantification of uncertainties induced via simulation-based modeling. Reliab Eng Syst Saf 133(133):79–86

Saroglou C, Bar N (2020) The ARMR classification system and the modified Hoek-Brown failure criterion compared to directional shear strength models for anisotropic rock masses. Period Polytech-Civil Eng 64(1):14–19

Shi J, Guo K, Xie B (2010) In: Xi YM (ed) Research on an error eliminating model enterprise for customer knowledge management, pp 205–209

Shi S, Li S, Li L, Zhou Z, Wang J (2014) Advance optimized classification and application of surrounding rock based on fuzzy analytic hierarchy process and tunnel seismic prediction. Autom Constr 37: 217–222

Si L, Wang Z, Jiang G (2019) Fusion recognition of shearer coal-rock cutting state based on improved RBF neural network and D-S evidence theory. IEEE Access 7:122106–122121

Tunsakul J, Jongpradist P, Kim H, Nanakorn P (2018) Evaluation of rock fracture patterns based on the element-free Galerkin method for stability assessment of a highly pressurized gas storage cavern. Acta Geotech 13(4):817–832

Wang J, Guo J (2019) Research on rock mass quality classification based on an improved rough set-cloud model. IEEE Access 7:123710–123724

Wang M, Xu X, Li J, Jin J, Shen F (2015) A novel model of set pair analysis coupled with extenics for evaluation of surrounding rock stability. Math Probl Eng 2015(1):1–9

Wang Y, Zhao N, Jing H, Meng B, Yin X (2016) A novel model of the ideal point method coupled with objective and subjective weighting method for evaluation of surrounding rock stability. Math Probl Eng 2016(4):1–9

Wu S, Chen J, Zhou Z, Yang S (2015) Application of reduced concept lattice and fuzzy optimum selection in rock mass quality evaluation of underground engineering. J Cent South Univ 46(10):3872–3878

Yao J, Yao B, Li L, Jiang Y (2012) Hybrid model for displacement prediction of tunnel surrounding rock. Neural Netw World 22(3): 263–275

Zhang M, Zhang Y (2018) Stability evaluation method for gateways in closely spaced coal seams and surrounding rock control technology. Arab J Sci Eng 43(10):5469–5485

Zhang N, Wang W, Yang Z, Zhang J (2017) Numerical simulation on the stability of surrounding rock of horizontal rock strata in the tunnel. Civil Eng J-Tehran 3(12):1188–1197

Zhang Q, Liu C, Duan K, Zhang Z, Xiang W (2020) True three-dimensional geomechanical model tests for stability analysis of surrounding rock during the excavation of a deep underground laboratory. Rock Mech Rock Eng 53(2):517–537

Zhao G, Chen A, Lu G, Liu W (2020) Data fusion algorithm based on fuzzy sets and D-S theory of evidence. Tsinghua Sci Technol 25(1): 12–19

Zheng J, Yang X, Lu Q, Zhao Y, Deng J, Ding Z (2018) A new perspective for the directivity of rock quality designation (RQD) and an anisotropy index of jointing degree for rock masses. Eng Geol 240:81–94

Zhou J, Li X (2012) Integrating unascertained measurement and information entropy theory to assess blastability of rock mass. J Cent South Univ 19(7):1953–1960

Zhou T, Hu J, Kuang Y, Huang R (2019) Improved rock engineering system (RES)-multidimensional cloud evaluation model and its application to the rock mass blastability. IEEE Access 7:100305–100317

Zhu X, Wang Y, Ren Y (2020) Numerical simulation to research on the fracture mechanism of the surrounding rock in deep tunnels. Geotech Geol Eng 38(1):319–327