



Evaluation model of surrounding rock stability based on fuzzy rock engineering systems (RES)-connection cloud

Yuxu Gao^{1,2} · Feng Gao^{1,2} · Keping Zhou^{1,2}

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Abstract

The factors affecting the stability of surrounding rock have fuzzy randomness, and their evaluation indicators not only show boundary ambiguity and interval discreteness but also have complex interactions. In order to reflect the distribution characteristics and interaction relationship of the indicators, and improve the accuracy of surrounding rock stability evaluation, a stability evaluation model of surrounding rock based on a fuzzy Rock Engineering Systems (RES)-connection cloud is proposed. The research showed that the introduction of linguistic hesitant fuzzy sets improves RES, resulting in experts' compilation completely retained. Through cloud theory transformation, the subjectivity can be further weakened, and the credibility of indicator weight can be effectively improved. The two-dimensional cloud cause-effect map can reflect the indicator interaction relationship more intuitively and accurately. The joint state is found to be the most dominant parameter, and groundwater seepage is found to be the least dominant parameter. Furthermore, the connection cloud can overcome the defects of traditional cloud model which assumes the indicator follow normal distribution. Comparing the engineering application results with the matter-element extension method and the fuzzy set method, the feasibility of the present model is verified.

Keywords Cloud transformation · Connection cloud · Fuzzy RES, · Linguistic hesitation fuzzy set · Surrounding rock stability

Introduction

The classification of surrounding rock stability can provide important information for engineering design and construction method selection, and it has important guiding significance for rock excavation and support. The growing demand for engineering has resulted in the development of rock mass stability classification as an independent discipline. Finding a suitable classification method of surrounding rock stability for engineering applications has always been one of the important research directions in rock mechanics. The existing methods for evaluating surrounding rock stability can be divided into three categories—qualitative analysis, quantitative analysis, and meta-analysis. With the development of rock mechanics

theory and evaluation algorithms, quantitative analysis has gradually replaced qualitative analysis.

Evaluation methods range from single-index methods (e.g., Rock Quality Designation (RQD) and the Rock Mass Rating (RMR) system)(Zhang et al. 2019) to methods utilizing the comprehensive evaluation of multiple indicators, e.g., the catastrophe progression method (Xie et al. 2018), uncertainty measurement theory(He et al. 2014; Li et al. 2017), back propagation (BP) neural networks(Liu et al. 2018; Gao et al. 2018; Tian et al. 2017; Goh and Zhang 2012), matter-element extension analysis theory(Su et al. 2006), fuzzy set contrastive analysis theory (Wang et al. 2015), set pair analysis(Bu et al. 2018), fuzzy comprehensive evaluation method (Wang et al. 2017), the data-driven Multivariate adaptive regression spline method(Zhang and Goh 2012; Goh et al. 2017), and the cloud model(Zhu et al. 2019; Wang et al. 2016). And also include a combination of various theories for evaluation, e.g., particle swarm optimization combined with a support vector machine algorithm(Nie et al. 2013; Zhuang et al. 2019; Liu et al. 2017), and fuzzy comprehensive evaluation combined with numerical simulation(Ding et al. 2019). Although some achievements have been made, each method has its own drawbacks. For example, the matter-element extension method ignores the

✉ Feng Gao
csugaofeng@csu.edu.cn

¹ School of Resource and Safety Engineering, Central South University, Changsha 410083, Hunan, China

² Research Center for Mining Engineering and Technology in Cold Regions, Central South University, Changsha 410083, Hunan, China

uncertainty of the indicator, and its effect on dealing with the discrete optimization problem is poor. The cloud model realizes the fuzzy transformation of qualitative and quantitative indicators, but the traditional cloud model assumes that the evaluation indicator satisfies the normal distribution, however, in actual engineering, the individual effects of the factors are not uniformly small, that is, some indicators have an overriding dominant role, and the indicators are not independent of each other but have a certain degree of interdependence, they will not be able to meet the conditions of normal distribution; meanwhile, the stability classification based on traditional cloud is excessively affected by the indicators at the mean of the interval. These shortcomings affect the accuracy of the surrounding rock stability evaluation.

On the contrary, the stability of the surrounding rock is affected by multiple indicators, which are not completely independent but have interaction with each other. Together, they constitute a complex fuzzy system and ultimately determine the stability classification of the surrounding rock. The rock engineering system (RES, Hudson 1992) is an approach to deal with complex engineering problems, as it combines adaptability, comprehensiveness, repeatability, efficiency, and effectiveness. Many researchers attempted to develop this method in various fields, such as Shang et al. (2000) and Rozos et al. (2011) used RES coupled with GIS to solve the site selection problem, Zhang et al. (2004), Montoya-Montes et al. (2012), Rozos et al. (2008), Yoo et al. (2008) and Ali and Hasan (2002) adopted RES approach to evaluate the stability of slope and tunnel. In addition to geological applications, many researchers applied RES to various practical engineering problems, such as Andrieux and Hadjigeorgiou (2008) assessed the likelihood of success of a large-scale confined distress blast in an underground mine pillar using RES, Saeidi and Khalokakaie (2013) predict the groutability of the rock mass based on RES method, and Fattahi and Moradi (2018) estimated the rock mass deformation modulus based on RES. In all these studies, the traditional RES was used to obtain the weight and interaction relationship of every factors, and the key factors in the index system can be found. The quantification of the interaction strength in matrix is one of the most important parts of the RES method, in all of the above studies, the expert semi-quantitative method (ESQ) is the commonly used, in which one value is deterministically assigned to each interaction, relying on the expert experience to assign the interaction matrix. Therefore, the ESQ implicitly consider that there are no uncertainties when the influence of one indicator on the others, the main weakness of ESQ is its great variability of interaction value and rough correspondence between value and action strength. Rafiee et al. (2015, 2016) introduced the fuzzy system theory to minimize subjectivity of quantifying the interaction matrix, but it caused the loss of some expert's evaluation information, and its *C-E* map cannot reflect the fuzzy interaction of the indicators.

In view of this, in this study, a novel coding approach is proposed for use within the RES systems framework. In this method, in order to completely retain the experts' evaluation information, the linguistic hesitation fuzzy set was used to coding the interaction matrix. Then in order to weaken the coding subjectivity and integrate the coding results, using the cloud model theory, the semi-quantitative linguistic variables in comprehensive interaction matrix are transformed into the fuzzy quantitative variables in comprehensive cloud form. Finally through decoding the interaction matrix, we can learn the interaction of indicators, and the indicator weights are determined. Considering that in practice, the distribution of evaluation indicators of surrounding rock stability is in the form of a limitation interval distribution, the randomness, and fuzziness reflected by the traditional cloud model are different from the actual situation, which is most obvious in the distribution of the membership degree of the boundary level (the highest and the lowest risk grade); thus, the connection cloud theory is introduced to overcome this defect. The improved RES is coupled with the connection cloud to establish a stability evaluation model for the surrounding rock. The validity of the model is verified by engineering cases.

Research method

RES theory

RES theory (Hudson 1992) begins with the evaluation indicators that interact with each other and work together on the same research object. The specific mechanism and framework of RES was listed in appendix A. In the traditional RES, the interactive matrix (Fig. 4 in Appendix A) compilation method is the ESQ method, which quantifies the evaluation tone simply into specific values. Natural language, however, does not strictly distinguish between randomness and fuzziness, but includes both. For example, in the use of words such as “probably,” “maybe,” “or so”, and “more or less,” fuzziness implies randomness and randomness implies fuzziness (Li and Du, 2005). The ESQ method obviously lacks the description of the uncertainty and ambiguity of the interaction strength between indicators. Therefore, in this paper, to overcome the loss and distortion of information, the linguistic hesitation fuzzy set is applied to compile the interaction matrix and perform cloud transformations on the compilation results.

Hesitant fuzzy linguistic set and cloud transformation

The hesitant fuzzy set (HFS) is used in quantitative situations in which people hesitate about several possible values to determine the membership degree of an element to a given set (Tang and Liao 2019). Motivated by the HFS, Rodriguez et al. (2012) introduced the Hesitant fuzzy linguistic term

set(HFLTS) to express qualitative information in which people hesitate about several linguistic terms.

Definition 1: Let $S = \{s_0, s_1, \dots, s_{t-1}\}$ be a linguistic term set, where t is an odd number, a linguistic hesitant fuzzy set in S is a set that when applied to the linguistic terms of S returns a subset of S with several values in $[0, 1]$, denoted by $LH = \{<S_{\theta(i)}, lh(S_{\theta(i)})> | S_{\theta(i)} \in S\}$, where $lh(S_{\theta(i)}) = \{r_1, r_2, \dots, r_{m_i}\}$ is a set with m_i values in $[0, 1]$ denoting the

possible membership degrees of the element $S_{\theta(i)} \in S$ to the set LH .

In this study, let $t = 4$; then the linguistic term S_0, S_1, S_2, S_3, S_4 , means: no influence, weak influence, medium influence, strong influence, and decisive influence, respectively. The universe is $[X_{\min}, X_{\max}]$; by the golden ratio method (Zhu et al. 2016), five clouds can be generated with their numerical characteristics as $A_i(Ex_i, En_i, He_i)$ ($i = 1, 2, \dots, 5$):

$$\begin{cases} Ex_2 = (X_{\min} + X_{\max})/2, Ex_0 = X_{\min}, Ex_4 = X_{\max}, \\ Ex_1 = Ex_2 - 0.382(X_{\max} - X_{\min})/2, Ex_3 = Ex_2 + 0.382(X_{\max} - X_{\min})/2; \\ En_1 = En_3 = 0.382(X_{\max} - X_{\min})/6, En_2 = 0.618En_3, En_0 = En_4 = En_3/0.618; \\ He_1 = He_3 = He_2/0.618, He_0 = He_4 = He_3/0.618 \end{cases} \tag{1}$$

The universe of this study is taken as $[0, 10]$, $He_2 = 0.1$. Using Eq. (1), we can obtain the following five clouds: $A_0(0, 1.031, 0.262)$, $A_1(3.09, 0.637, 0.162)$, $A_2(5, 0.393, 0.1)$, $A_3(6.91, 0.637, 0.162)$, $A_4(10, 1.031, 0.262)$.

Definition 2: Let $S = \{s_0, s_1, \dots, s_{t-1}\}$ be a linguistic term set, where the valid universe is $[X_{\min}, X_{\max}]$. The cloud $A_i(Ex_i, En_i, He_i)$ represents S_i . Let $LH = \{<S_{\theta(i)}, lh(S_{\theta(i)})> | S_{\theta(i)} \in S\}$ be a linguistic hesitant fuzzy set, where $lh(S_{\theta(i)}) = \{r_1, r_2, \dots, r_{m_i}\}$. $A_{LH}^*(Ex_{LH}^*, En_{LH}^*, He_{LH}^*)$ is called the comprehensive cloud (Rozos et al. 2011) of LH , where

$$\begin{cases} Ex_{LH}^* = \frac{1}{|LH|} \left(\sum_{\theta(i) \in LH} \frac{Ex_{\theta(i)}}{|lh(S_{\theta(i)})|} \left(\sum_{r \in |lh(S_{\theta(i)})|} r \right) \right), \\ En_{LH}^* = \sqrt{\frac{1}{|LH|} \sum_{\theta(i) \in LH} (En_{\theta(i)})^2}, \\ He_{LH}^* = \sqrt{\frac{1}{|LH|} \sum_{\theta(i) \in LH} (He_{\theta(i)})^2} \end{cases} \tag{2}$$

The comprehensive cloud unifies the form of (HFLTS) with different lengths, which is conducive to generalizing the decision making methods to linguistic fuzzy decision-making (Wang and Feng 2005).

Connection cloud model

The actual distribution of evaluation indicators often presents a limited interval distribution rather than an ideal normal distribution; thus, the randomness and fuzziness expressed by traditional cloud models are different from the actual parameters. The connection cloud model overcomes this weakness and it is more in line with the distribution characteristics of surrounding rock stability evaluation indicators in actual situation.

Connection cloud (Wang et al. 2016) definition: Assume that the classification standard can be divided into m evaluation grades ($i = 1, 2, \dots, m$), each grades has n evaluation indexes ($j = 1, 2, \dots, n$), the cloud mapping of grade i for index j consists of both the left and right half of an asymmetric connection cloud with the boundary of expected value Ex^j , and the cloud drop is obtained by the digital feature values (Ex, En, He, a, λ) and the cloud drop N , which can be expressed by

$$u_i = \left[1 - \left(\frac{x_i - E_x^i}{a_i'} \right)^2 \right]^{\lambda_i} \tag{3}$$

$$a_i' = En^i \sqrt{2\lambda_i + 3} \tag{4}$$

$$\lambda_i = \frac{\lg 0.5}{\lg \left[1 - \left(\frac{y_i - E_x^i}{a_i'} \right)^2 \right]} \tag{5}$$

$$E_x^i = \frac{L_{\max}^i + L_{\min}^i}{2} \tag{6}$$

$$E_n^i = \frac{a_i}{\sqrt{2\lambda_i + 3}} \tag{7}$$

$$He^i = 0.1Ex^i \tag{8}$$

Where Ex^i, En^i , and He^i are expected value, entropy, and hyper entropy of the left interval or right interval of grade i in the asymmetric connection cloud, respectively; a_i and a_i' are the half-interval length and modified half-interval length, (a_i' denotes the modified left half-interval length, $x_i \in [Ex^i - a_i', Ex^i]$, and a_i denotes the modified right half-interval length, $x_i \in [Ex^i, Ex^i + a_i]$, in which En^i is generated by a normal distribution, $En^i \sim N(En^i, (He^i)^2)$; L_{\max}^i and L_{\min}^i are the upper limit and lower limit of the interval in the i th evaluation grade, respectively; and λ_i is the order of the corresponding distribution density function

Table 1 Classification of surrounding rock stability evaluation indicators

Grade	$RQD(\%), X_1$	$R_w(\text{MPa}), X_2$	K_v, X_3	$W(\text{L}/(\text{min}\cdot 10\text{ m})^{-1}), X_4$	Joint condition, X_5
I	60–100	200–300	0.75–1.00	0–5	9–10
II	40–60	100–200	0.55–0.75	5–10	7–9
III	25–40	50–100	0.30–0.55	10–25	4–7
IV	10–25	25–50	0.15–0.30	25–125	2–4
V	0–10	0–25	0–0.15	125–250	0–2

Evaluation model for surrounding rock stability based on fuzzy RES-connection cloud

Surrounding rock evaluation indicator system

The classification of surrounding rock stability is closely related to the selection of evaluation indicator, and its influencing factors are mainly geological factors and engineering factors. Geological factors mainly include rock mass characteristics, groundwater activity, stress state and joint state of surrounding rock, while engineering factors refer to external factors that are formed in the later stage of rock mass without disturbance. In this paper, we focus on the characteristics of surrounding rock before engineering activities, so the evaluation indicators are selected from geological factors. According to the relevant research results(Xue et al. 2019; Hu 2000; Rehman et al. 2018), considering the accessibility of indicators, the rock quality index RQD (%), uniaxial compressive strength R_w (MPa), rock integrity index K_v , groundwater seepage volume W (L/(min·10 m)) and joint condition are used as the evaluation indicators of surrounding rock stability, in which the surrounding rock properties are reflected by RQD , uniaxial compressive strength, and the rock integrity index. The groundwater seepage volume is used to reflect the softening and destructive effects of groundwater on surrounding rock. The stability of surrounding rock is divided into five grades: grade I (extremely stable), grade II (stable), grade III (basic stability), grade IV (unstable), and grade V (very unstable). The corresponding indicators are also divided into five grades, and the specific classification criteria are shown in Table 1.

Rock quality index (RQD) can reflect the development characteristics of structural plane. In engineering, rock mass quality is judged according to the integrity of drilling core, that

is, the cumulative length of core over 10 cm (including 10 cm) is the percentage of the total length of borehole (Table 1).

Uniaxial compressive strength (UCS) is one of the most important engineering properties of rocks, which represents the ability of resist deformation. Rock material strength is used as a crucial parameter in many rock classification systems. UCS is influenced by many characteristics of rocks such as weathering or alteration rate, micro cracks and internal fractures, density and porosity (Singh and Goel 2011). Based on the RMR classification, the unconfined compressive strength of intact rock is subdivided into five classes (Table 1).

Rock integrity index (K_v) is an important index reflecting rock integrity. The development degree of structural planes (joints, layers, gneisses, faults) in rock mass (i.e., rock mass integrity) is an important geological factor affecting the stability of surrounding rock mass. The engineering properties of rock mass largely depend on the weak structural planes and fillers between them, as well as their spatial distribution, including the number of structural planes, spacing, and the number of joints per unit volume. They directly weaken the stability of surrounding rock. It can be obtained by wave velocity test for qualitative evaluation. Expressed by Eq. (9):

$$K_v = (V_{pm}/V_{pr})^2 \tag{9}$$

Where, V_{pm} is the P wave velocity of rock mass and V_{pr} is the P wave velocity of complete rock mass.

Groundwater is an important factor affecting the stability of surrounding rock. The influence of groundwater on the stability of surrounding rock is mainly manifested in the following three aspects: (1) groundwater softens the rock and reduces the strength of the rock, which is most obvious to the rock in the weathered fractured zone, and reduces the self-

Table 2 Criteria for joint surface coefficient

Level	Description of joint surface	Value
I	Very rough surface, discontinuous, closed rock wall	9~10
II	Micro-rough, surface opening <1 mm, slightly weathered	7~9
III	Micro-rough, surface opening <1 mm, seriously weathered	4~7
IV	Slip surface or mud with thickness less than 5 mm, surface opening between 1 and 5 mm	2~4
V	Mud with thickness > 5 mm, surface opening >5 mm	0~2

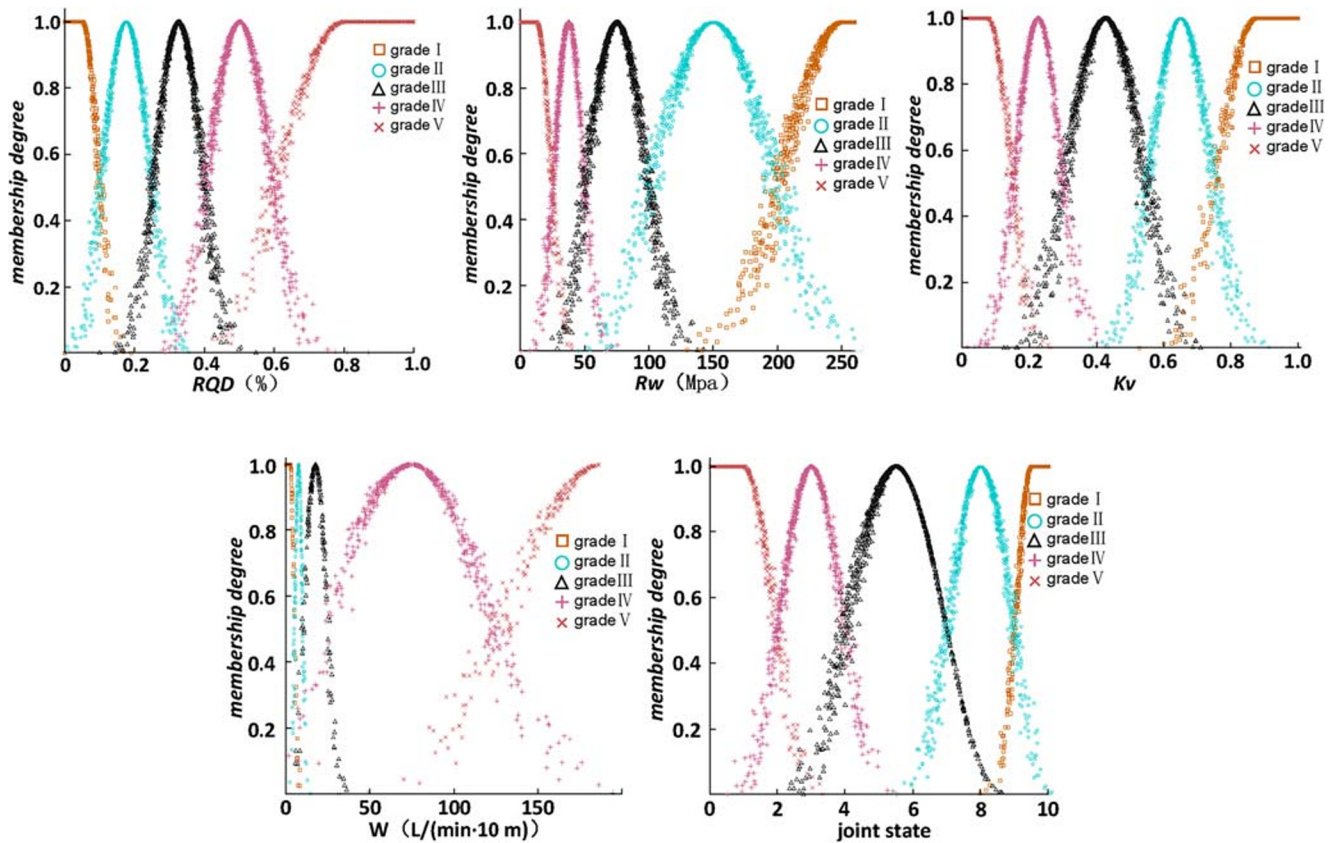


Fig. 1 Standard connection clouds of evaluation indicators classification

stabilization ability of surrounding rock; (2) In rock mass with weak structural planes, water will reduce the friction of structural planes, dissolve the cements between rocks, and induce the sliding and failure of rock mass. (3) Increase the dynamic and static water pressure, and the water may contain corrosive substances, which have corrosive effect on surrounding rock and supporting structure. Therefore, the seepage volume per minute of 10 m long surrounding rock is chosen as the basis for quantitative determination of groundwater.

Joint condition contains the joints' distribution, development, scale, and physical and mechanical properties, and it is closely related to rock mass strength and stress state. The degree of joint openness and filling properties are important components for determining rock mass integrity (Xue et al. 2019). Joint condition is a single-factor evaluation criterion to

quantitatively evaluate joint surface properties, which can be achieved through a geological sketch of the tunnel face (Table 2).

According to the classification standard of the surrounding rock stability evaluation indicator (Table 1), based on the connection cloud theory, all the indicator cloud digital characteristics of five grades can be obtained according to Eq. (3)–(8); according to Eq. (3), 500 cloud droplets in each of the left and right half intervals of the j index i level are simulated, and a connection cloud of the j index i level is generated, as shown in Fig. 1. In the figure, the abscissa is the value of the evaluation indicator, and the ordinate is the membership degree. The five clouds in each figure represent the standard connection cloud of the I–V grade, connection cloud is more superior on the assumption of indicator distribution. For example, the

Table 3 Indicator linguistic hesitation fuzzy set synthesis interaction matrix

Index factors of surrounding rock stability classification system				
X_1	$\{(S_2, 0.4, 0.5, 0.6)\}$	$\{(S_2, 0.6), (S_3, 0.7, 0.8)\}$	$\{(S_1, 0.3, 0.4), (S_2, 0.5)\}$	$\{(S_1, 0.4, 0.5), (S_2, 0.4)\}$
$\{(S_1, 0.5, 0.6, 0.7)\}$	X_2	$\{(S_0, 0.7, 0.8), (S_1, 0.8)\}$	$\{(S_1, 0.5, 0.7), (S_2, 0.4)\}$	$\{(S_1, 0.5, 0.7, 0.8)\}$
$\{(S_3, 0.7, 0.7, 0.8)\}$	$\{(S_2, 0.8), (S_3, 0.7, 0.7)\}$	X_3	$\{(S_3, 0.8), (S_4, 0.6, 0.7)\}$	$\{(S_3, 0.6, 0.7), (S_4, 0.5)\}$
$\{(S_1, 0.3, 0.4, 0.5)\}$	$\{(S_1, 0.5, 0.6, 0.7)\}$	$\{(S_1, 0.6, 0.7, 0.8)\}$	X_4	$\{(S_0, 0.5, 0.8), (S_1, 0.6)\}$
$\{(S_3, 0.5, 0.7, 0.7)\}$	$\{(S_2, 0.6, 0.7), (S_3, 0.5)\}$	$\{(S_3, 0.5, 0.7, 0.8)\}$	$\{(S_2, 0.8), (S_3, 0.6, 0.7)\}$	X_5

Table 4 The comprehensive cloud interaction matrix of the surrounding rock stability indicators

Index factors of surrounding rock stability classification system				
X_1	2.500 0.393 0.100	4.091 0.748 0.190	1.791 0.748 0.190	1.690 0.748 0.190
1.854 0.637 0.162	X_2	1.236 1.212 0.308	1.927 0.748 0.190	2.061 0.637 0.162
5.067 0.637 0.162	4.419 0.748 0.190	X_3	6.014 0.212 0.308	3.496 1.212 0.308
1.236 0.637 0.162	1.857 0.637 0.162	2.163 0.637 0.162	X_4	0.927 1.212 0.308
4.376 0.637 0.162	3.353 0.748 0.190	4.607 0.637 0.162	4.246 0.748 0.190	X_5

RQD value expectation of grade V is 80, when the measured data of *RQD* is greater than 80, the membership of the grade V should still be 1, but in the traditional cloud, the boundary grade cloud (the highest and lowest grade) distribution still presents a normal distribution, thus, when the *RQD* value is greater than 80, its membership begins to decrease, which is obviously not consistent with the actual situation.

Comprehensive evaluation based on fuzzy RES

The procedure for building the interaction matrix is as follows. Invite relevant experts in this field to compile the interaction matrix of indicators. To preserve the information implied by “probably” “maybe” in evaluation, applying the linguistic hesitation fuzzy set, compile an interaction matrix. The linguistic term set is S_0, S_1, S_2, S_3, S_4 , which means no influence, weak influence, medium influence, strong influence, and decisive influence, respectively. Integrate multiple interaction matrices into a comprehensive indicator interaction matrix, as displayed in Table 3.

When the experts code the interaction matrix, the concept of linguistic terms used does not strictly distinguish between randomness and ambiguity but includes both. The linguistic hesitant fuzzy set semi-quantizes a large number of words

such as “probably,” “maybe,” and “or so” through membership degree. Therefore, to further consider the randomness of the relationship between indicators and weaken expert subjectivity, cloud theory is introduced to achieve the transformation from qualitative and semi-quantitative data to quantitative data. The universe of the linguistic hesitant fuzzy set is taken as $[0,10]$ in this study. According to the numerical characteristics of five clouds (A_0-A_4) in the linguistic hesitant terminology set, the linguistic hesitant decision matrix (Table 3) is transformed into the comprehensive cloud interaction matrix according to Eq. (2), as listed in Table 4.

To decode the comprehensive cloud interaction matrix, the addition operation of cloud theory should be introduced, and its operation mode is as follows (Zhu et al. 2016). If there are clouds $A_1 (Ex_1, En_1, He_1)$ and $A_2 (Ex_2, En_2, He_2)$ in a certain domain U , then the result of the additive algebra operation is $A(Ex, En, He)$ such that

$$Ex = Ex_1 + Ex_2 \tag{10}$$

$$En = \sqrt{En_1^2 + En_2^2} \tag{11}$$

$$He = \sqrt{He_1^2 + He_2^2} \tag{12}$$

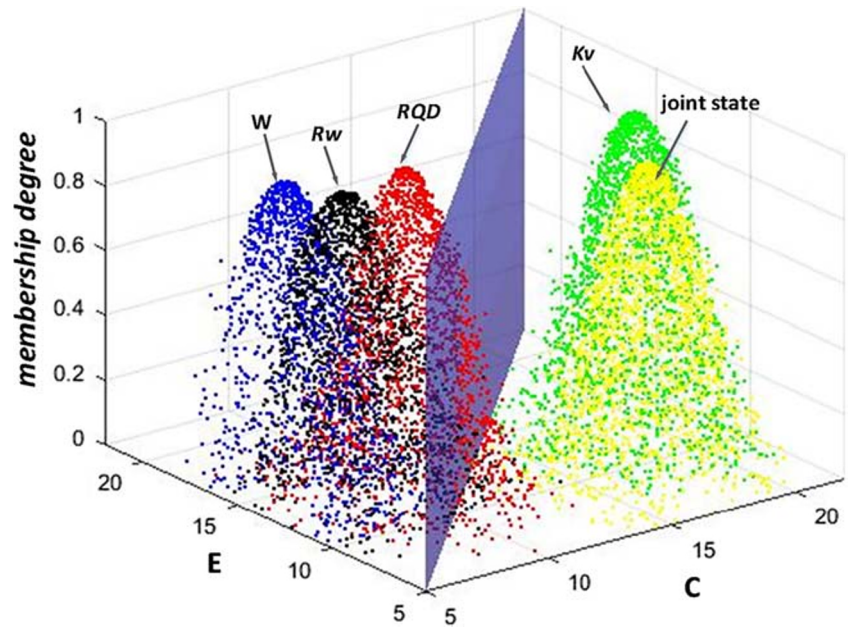
The cloud coding of the row and column in which indicator P_i is located is added to obtain the cloud coding of cause (C) and effect (E) in the index interaction matrix, as well as the interaction strength ($C + E$) with the system. On this basis, the weights (w_i) of each evaluation indicator are expressed by Eq.(10–12) and Eq.(13 in Appendix A), as displayed in Table 5.

In order to visually express the fuzzy interactive relationship between indicators, using the two-dimensional cloud generator, the two-dimensional cloud of five indicators, where the two interacting dimensions values are C and E cloud coding values, is generated, and the cause-effect ($C-E$) map of the surrounding rock stability indicators is generated, as shown in Fig. 2. The x -axis is the cause (C), the y -axis is the effect (E), and the z -axis is the membership degree. The interaction between the indicators is illustrated by the specific spatial distribution of the indicators in the $C-E$ map. The plane perpendicular to the $x-y$ coordinate system with the edge of $C = E$ is the equivalent plane of the causal space, which divides the space into upper left and lower right parts. The indicator located in

Table 5 Surrounding rock stability grading indicators

Index factors	C	E	$C + E$	w_i (%)
<i>RQD</i> (%), X_1	10.07 1.354 0.3439	12.53 1.936 0.4922	22.61 2.363 0.6004	19.19
R_w (MPa), X_2	7.078 2.194 0.5575	12.13 1.235 0.3140	19.21 2.518 0.6399	16.30
K_v , X_3	18.99 1.525 0.4922	12.10 1.685 0.4283	31.09 2.273 0.6524	26.39
$W(L/(min \cdot 10 m)^{-1})$, X_4	6.182 1.936 0.4922	13.98 1.623 0.5118	20.16 2.526 0.7100	17.11
Joint state, X_5	16.58 1.389 0.3531	8.174 1.976 0.5021	24.76 2.415 0.6138	21.01

Fig. 2 C–E indicator interactive cloud map



the lower right area has a greater advantage to the surrounding rock stability grading system. The indicator in the upper left area has a weaker parameter advantage for the system. It can be seen from the figure that the joint condition is the greatest advantage parameter; its effect on the indicator system is greatest; the groundwater seepage (*W*) is the least dominant parameter, which is the most affected by the others. The expectation of *RQD* is on the upper left side of the split plane, but the $C = E$ plane partially cuts its two-dimensional cloud, which means that the interaction role of *RQD* has fuzziness and randomness, so the effect of this indicator on the system is roughly equal to that of the system. Compared with the traditional RES *C-E* diagram (Rafiee et al. 2016), the two-dimensional cloud model replaces the determined coordinate points, which is more conducive for visually depicting the specific interaction of each indicator in the surrounding rock stability system. The situation realizes the ambiguity and random expression of the complex fuzzy system, which reflects the advantages of cloud transformation.

Stability evaluation of surrounding rock based on fuzzy RES-connection cloud

The implementation process of the surrounding rock stability evaluation model based on the fuzzy RES-connection cloud is as follows. First, several experts are invited to compile the indicator interaction matrix based on linguistic hesitant fuzzy set theory. The coding results are integrated, thus all expert comment information is retained. Realize the fuzzy transformation from qualitative and half-qualitative to quantitative data (type 3) based on the cloud model, weakening the subjectivity of expert evaluation, and the weights of every

indicator is obtained by Eq. (1). Next, the evaluation index system of surrounding rock stability is established. The I–V grade connection cloud digital features (Ex, En, He, a, λ) of each indicator are obtained based on the connection cloud, and the cloud generator is used to generate the asymmetric grade connection cloud of each indicator. Finally, the measured values of the cases to be evaluated are substituted into the connection cloud model to obtain the five grade

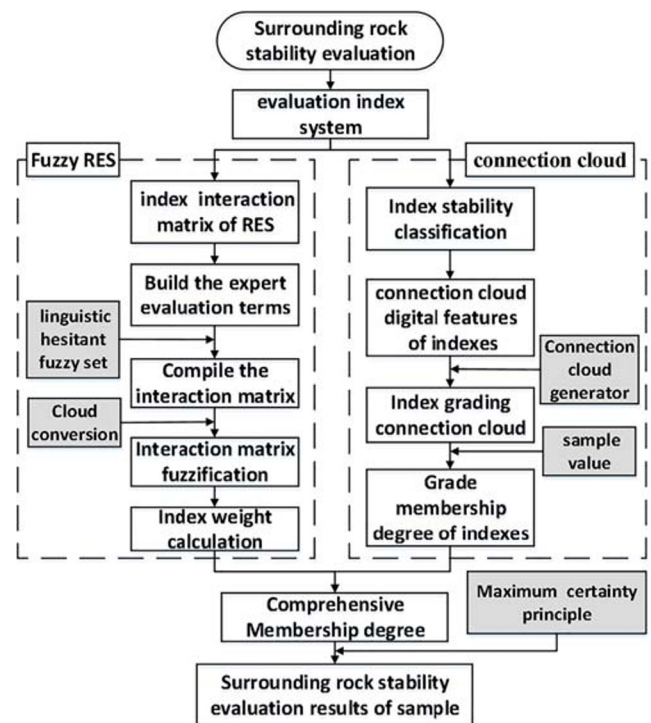


Fig. 3 Evaluation model of surrounding rock stability based on fuzzy RES-connection cloud

Table 6 Measured values of evaluation indicators

Sample	X_1 RQD(%)	X_2 R_w (MPa)	X_3 K_v	X_4 W (L/(min·10 m) ⁻¹)	X_5 Joint condition
1	0.12	185.5	0.89	6	8
2	0.27	176.4	0.80	8	7
3	0.08	158.2	0.94	6	7
4	0.04	201.1	0.97	5	9
5	0.24	181.9	0.92	9	8
6	0.52	25.0	0.22	20	4
7	0.26	40.0	0.38	10	6
8	0.26	25.0	0.15	20	3

membership degrees of each indicator. Combined with the indicator weight, the membership degree of all indicators in each grade are weighted and added; according to the “maximum membership degree principle,” the sample stability grade is determined. The specific process is shown in Fig. 3.

Case study

To verify the feasibility of the proposed model, the stability of surrounding rock of a mine in Shanxi Province of China is evaluated. Two fault fracture zone named F3 and F12 cut into the mine from its southwest end. One strikes N25°~40°E and dips to SE, another strikes N29°W and dips to NE. The both dips angle are between 15° and 19°. The fault throws of F3 and F12 are unequal, which in middle is large and the ones in two ends are small, and the extension lengths are 6000 m and 1300 m respectively. The surrounding rock stratum is the Taiyuan Formation of Upper Carboniferous. Its lithology is mainly gray-white medium-coarse quartz sandstone, and contains a small part of conglomerate. The rock is hard, displays massive structure and locally loose structure, and its joint fissures are not well developed. The -136 m tunnel face of the mine is selected as the actual evaluation section, and Table 6 is part of the measurement data collected based on the indicator system.

Substitute the sample data in Table 6 into the surrounding rock stability evaluation model based on fuzzy RES-connection cloud. The index weights were taken as $w_i = \{0.1919, 0.1630, 0.2639, 0.1711, 0.2101\}$, which were obtained in the study, and the stability grade of each sample was determined according to Eq. (3). The evaluation results and comparison with other methods are listed in Table 7.

It can be seen from Table 7 that compared with the classification results in (Lian et al. 2004; Hu 2000; Luo and Wang 2009), the evaluation results based on the fuzzy RES-connection cloud are basically consistent with the evaluation results of the matter element extension method and the fuzzy set method, thus the feasibility of the model is proved. According to the “maximum membership degree principle,” sample No. 1 is judged to be grade II, and the distance between the grade membership degree of II (0.5968) and I (0.4004) is much smaller than the distance between grade II and grade III (0.0277). Thus, it can be considered that the true classification of sample 1 should be between level II and level I, that is, it is determined to be level II but biased toward level I. Similarly, samples 2, 3, and 5 all have this feature. Furthermore, when the difference between the two adjacent levels of the sample theoretical level is small (<0.2, such as samples 6, 7, 8), or when the theoretical grade is at the lowest and highest

Table 7 Sample evaluation results and comparison

Sample	Comprehensive membership degree					Proposed model	Matter element extension(Lian et al. 2004; Hu 2000)	Fuzzy set(Luo and Wang 2009)
	$U(I)$	$U(II)$	$U(III)$	$U(IV)$	$U(V)$			
1	0.4004	0.5968	0.0277	0	0	II~I*	II	II
2	0.0988	0.6230	0.3268	0.0001	0	II~III*	II	II
3	0.4333	0.4648	0.1144	0	0	II~I*	II	II
4	0.7305	0.2782	0	0	0	I	I	I
5	0.3060	0.5828	0.1611	0	0	II~I*	II	II
6	0	0	0.2871	0.7010	0.1306	IV	IV	IV
7	0	0.1728	0.6717	0.1687	0.0017	III	III	III
8	0	0.0775	0.2719	0.4882	0.2201	IV	IV	IV

grade (such as sample 4), it can be considered that the bias of the grading is not obvious, and the theoretical grade is regarded as the true grade. Therefore, applying the judgment results of the model proposed in this study can provide more reference information for the evaluation of surrounding rock of actual engineering and the selection of surrounding rock support measures.

Conclusions

- 1) The linguistic hesitation fuzzy set was introduced to replace the ESQ coding method, then the cloud theory was used to convert data in linguistic hesitant fuzzy set form into the fuzzy quantitative integrated cloud data, weakening the subjectivity in the RES coding and improving the accuracy of the indicator weights.
- 2) The cause-effect (C-E) map of the traditional RES was improved to two-dimensional cloud map based on cloud theory, the fuzzy and random interaction of factors was intuitively and truly reflected.
- 3) Coupled improved RES with connection cloud, the surrounding rock stability was accurately evaluated. Through comparison and verification, this model can more accurately and effectively reflect the true stability grade and its classification bias.

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Appendix

RES theory

RES theory (Hudson 1992) begins with the evaluation indicators that interact with each other and work together on the same research object. Using a binary action mechanism to reflect the interaction between the evaluation indicators, the complex system morphology of the research object is described using the indicator system interaction matrix. By coding the non-diagonal elements of the interaction matrix and analyzing the interaction matrix, the interaction relationship between the indicators can be obtained, as well as the interaction strength of different indicators on the fuzzy complex system of the research object, so as to realize the identification of the main factors of the system and the importance (i.e., the weight) of the indicators. Figure 4 shows the multidimensional interaction matrix ($N \times N$), which contains N evaluation indicators,

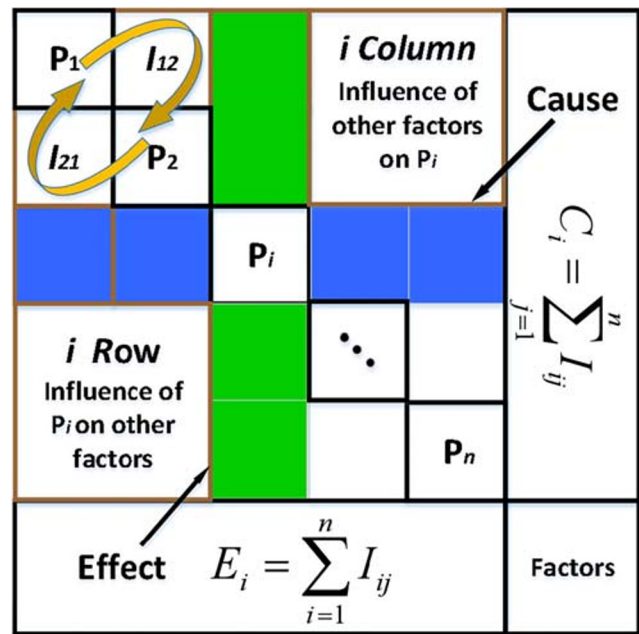


Fig. 4 Multidimensional indicator interaction matrix of RES

where the N elements on the main diagonal are evaluation indicators, and the elements on the off-diagonal are the interaction values between the indicators, the interaction direction of the indicators is as shown by the clockwise circle in the upper left corner, and I_{ij} and I_{ji} are the effect code values of P_i to P_j and P_j to P_i , respectively. The sum of the influence code values of the row where P_i is located reflects the intensity of the influence of P_i on the remaining indicators, which is called the cause C_i , and the sum of the influence code values of the column where P_i is located reflects the influence intensity of the remaining indicators on P_i , which is called the effect E_i . The importance of each evaluation index is obtained by comparing the $C_i + E_i$ values of each indicator, and the (C_i, E_i) reflects the interaction relationship between each indicator and the system. The weight w_i of each indicator is expressed as

$$w_i = \frac{C_i + E_i}{\sum_{i=1}^n (C_i + E_i)} \times 100\% \tag{13}$$

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