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An analytical model for assessing soft rock tunnel collapse risk and its engineering application

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Abstract. The tunnel collapse, large deformation of surrounding rock, water and mud inrush are the major geological disasters in soft rock tunnel construction. Among them, tunnel collapse has the most serious impact on tunnel construction. Current research backed theories have certain limitations in identifying the collapse risk of soft rock tunnels. Examining the Zhengwan high-speed railway tunnel, eight soft rock tunnel collapse influencing factors were selected, and the combination of indicator weights based on the analytic hierarchy process and entropy weighting methods was obtained. The results show that the groundwater condition and the integrity of the rock mass are the main influencing factors leading to a soft rock tunnel collapse. A comprehensive fuzzy evaluation model for the collapse risk of soft rock tunnels is being proposed, and the real-time collapse risk assessment of the Zhengwan tunnel is being carried out. The results obtained via the fuzzy evaluation model agree well with the actual situation. A tunnel section evaluated to have an extremely high collapse risk and experienced a local collapse during excavation, verifying the feasibility of the collapse risk evaluation model. The collapse risk evaluation model proposed in this paper has been demonstrated to be a promising and innovative method for the evaluation of the collapse risk of soft rock tunnels, leading to safer construction.

Keywords: soft rock tunnel; collapse risk factors; combination weights method; soft rock tunnel collapse; fuzzy evaluation model

1. Introduction

Transportation construction plays a significant role in a country's economic development. Tunnels have the benefits of reducing travel time and enhancing operational efficiency, which typically makes them the best choice for highway route planning. In recent years, China has made remarkable achievements in tunnel construction, which not only solved traffic issues but also promoted the development of construction technology. However, due to special geological characteristics or improper selection of construction methods, tunnel disasters, including water mud inrush, the large deformation of supporting structures, etc (Benardos and Kaliampakos 2004, Fall *et al.* 2006, Aliabadian *et al.* 2015). These types of accidents make the surrounding rock unstable, leading to the destruction of the supporting structure and eventual tunnel collapse. Therefore, the ability to predict adverse geological features in a planned tunnel path through appropriate investigative methods is indispensable. Especially for soft rock tunnels and karst tunnels, where preventing the initial destabilization is particularly crucial (Yoo 2016, Aliyu *et al.* 2018, Daraei and Zare 2018).

The current theoretical analysis of soft rock tunnel collapse risk mainly relies on limit theory. Yang and Huang (2011) used the Hoek brown failure criterion to establish the damage energy consumption function, and they proposed the critical depth expression method for shallow tunnel collapse. Based on this research, Huang and Yang (2011) minimized the objective function by using the variational method to obtain the upper bound solution for tunnel collapse. Different types of projects have their engineering characteristics, leading to the lack of pertinence in theoretical analysis applications.

Due to the availability of a large amount of sample data and the advantage provided by the ability to simulate the construction conditions, numerical simulation is considered to be a crucial method to improve theoretical research (Li *et al.* 2016, Hasanpour 2014, Fraldi and Guarracino 2011). Huang *et al.* (2013) utilized model experiments and numerical simulations to investigate the evolution law of rock mass failure at different weak interlayer locations. However, the accuracy of the numerical simulation results can not be guaranteed. The results obtained by numerical simulation are often only taken as a reference in the analysis process. In recent years, comprehensive geophysical prospecting technology has been widely adopted in tunnel risk detection (Choi *et al.* 2004, Jetschny *et al.* 2011). Liu *et al.* (2018) successfully predicted the unfavourable geological section of the tunnel through geophysical prospecting technology and proposed a relatively complete system to predict unfavourable geological features. Researchers and industry experts have found in their investigations that the nonlinear theory can be used to identify the precursors to unfavourable tunnel geology. Soft

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rock, which is characteristically loose, broken, low density, low strength, and has poor stability, is mainly composed of mudstone, carbonaceous mudstone, sandy mudstone, and siltstone. Therefore, the strength of the surrounding rock is a crucial factor in tunnel stability (Wang *et al.* 2019, Shang *et al.* 2018, Ma and Zoback 2017). Based on the uniaxial compressive strength characteristics of the rock mass, Shang *et al.* (2017) conducted a series of laboratory tests and introduced a new technique termed forensic excavation of rock masses for directly investigating discontinuity persistence. Moreover, soft rock has a loose structure, high porosity, strong expansion, and it easily disintegrates after the absorption of water. Therefore, the groundwater conditions have a significant influence on the stability of the surrounding rock (Ma and Zoback 2018).

The complexity of the causes of collapse in soft rock tunnels determines the diversity of investigation methods. Hence, in addition to conventional research methods, the comprehensive evaluation method is widely utilized to investigate soft rock tunnel collapses. Current comprehensive investigation methods mainly include fuzzy comprehensive evaluation theory, probability and statistical theory, machine learning (Mahdevari *et al.* 2013, Li *et al.* 2019). The advantage of probability and statistical theory is that the analysis and calculation process is simple, and the analysis results are intuitive. Meanwhile, the probability and statistical theory requires a large number of data as the basis for research and has a high requirement for the sample data's distribution and dispersion degree. Therefore, probability and statistical may easily lack the in-depth understanding of evaluation objects, which leads to a large error in evaluation results. Machine learning is an interdisciplinary subject that can effectively improve learning efficiency by simulating human learning and computer learning. Support vector machine, artificial neural network algorithm and decision tree algorithm are commonly used in machine learning. In large-scale database analysis, the support vector machine algorithm and decision tree algorithm have low learning efficiency. The neural network algorithm has a strong ability in data processing and high classification accuracy, and can fully explore the nonlinear relationship between variables. However, both methods have shortcomings. For example, in large-scale data analysis, the learning efficiency of machine learning is unstable and the running speed is slow. For small-scale data analysis learning, the calculation error of machine learning or probability and Statistical theory will increase. Therefore, in the face of different engineering problems, choosing the right analytical method is crucial.

This paper selected eight indexes for assessing the soft rock tunnel collapse risk by investigating the causes of tunnel collapse accidents. The weight of the assessment indexes was obtained through the analytic hierarchy process and the entropy weight method. The fuzzy comprehensive evaluation model for evaluating the risk of soft rock tunnel collapse was established, and the model was utilized to predict the collapse risk of the actual engineering. The soft rock tunnel collapse evaluation model proposed in this paper has critical practical significance for similar projects in collapse risk assessment.

2. Weight calculation method

2.1 Analytic hierarchy process

The analytic hierarchy process is a widely used method for calculating subjective weights. Relevant experts were asked to evaluate the importance of indexes on a scale of 1~9, and then compared the indexes to form the judgment matrix $G_{n\times n}$. Each element in $G_{n\times n}$ represents the importance of the index. The eigenvalues and eigenvectors of the judgment matrix are obtained according to Eq. (1), and the subjective weight vector e_i (e_1, e_2, …, e_n) is obtained by normalizing the eigenvector $\boldsymbol{\alpha}$ corresponding to the maximum eigenvalue $\lambda_{\max}$ (Kim *et al.* 2014, Hyun *et al.* 2015, Aalianvari *et al.* 2012).

$$G_{n\times n}=\begin{bmatrix} g_{1\to 1} & g_{1\to 2} & \cdots & g_{1\to n} \\ g_{2\to 1} & g_{2\to 2} & \cdots & g_{2\to n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n\to 1} & g_{n\to 2} & \cdots & g_{n\to n} \end{bmatrix} \tag{1}$$

$G_{i\to j}$ indicates the importance of the index G_i relative to the index G_j. The degree of importance of the i_{th} index compared with the j_{th} index is $1/G_{i\to j}$. The values of $G_{i\to j}$ are listed in Table 1.

In this paper, the maximum eigenvalue $\lambda_{\max}$ of the judgment matrix $G_{n\times n}$ and its corresponding eigenvector α are obtained by using the maximum eigenvalue method, as shown in Eq. (2).

$$G\cdot\alpha=\lambda_{\max}\cdot\alpha \tag{2}$$

To avoid contradictions in the importance ranking process due to multiple factors being involved in the decision-making process, the consistency test coefficient *CR* was introduced and defined as in Eq. (3).

$$CR=CI/RI \tag{3}$$

where *CI* is the consistency index and *RI* is the random consistency index. The *CI* can be used to measure the

Table 1 Value of $G_{i\to j}$

Value of $G_{i\to j}$	Interpretation
1	G_i and G_j are equally important
3	G_i is slightly more important than G_j
5	G_i is more important than G_j
7	G_i is significantly more important than G_j
9	G_i is absolutely more important than G_j
2, 4, 6, 8	An intermediate value of the adjacent judgment above

Table 2 The value of *RI*

Order (n)	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

*Note: n is the number of decision indexes degree of inconsistency of $G_{n\times n}$ and can be obtained by Eq. (4).

$$CI = \frac{(\lambda_{\max} - n)}{(n-1)} \tag{4}$$

Furthermore, RI is the random consistency index and is defined below in Table 2, where n is the number of indexes.

According to Eqs. (3)-(4), a consistency check was performed on the process of importance ranking. When $CR < 0.1$, the judgment matrix $I_{n\times n}$ is considered acceptably consistent. The weight vector e_i (e_1, e_2, …, e_n) can be obtained by normalizing the eigenvalue vector $\boldsymbol{\alpha}$ corresponding to the maximum eigenvalue $\lambda_{\max}$ (Eq. (5)).

$$e_i = \alpha_i / \sum_{i=1}^{n} \alpha_i \tag{5}$$

However, when CR>0.1, the judgment matrix $G_{n\times n}$ is considered unacceptable consistency in importance ranking, and it is necessary to modify the values in $G_{n\times n}$.

2.2 Entropy method

The entropy method was first introduced by Karl Pearson for random variables analysis and was later extended to many fields, including engineering location selection evaluation, industry risk analysis, and investment risk forecast. The information in the data sample of the decision-making index determined the sensitivity of the decision-making index to the evaluation results, i.e., the objective weight. Using the entropy weight method to calculate the objective weight of decision indexes comprises the following steps (Constantin *et al.* 2011, Felicísimo *et al.* 2013, Delgado and Romero 2016).

2.2.1 Normalize the learning data

The learning data samples of the decision indexes are essential in calculating the objective weight. Suppose there are m decision indexes and n sets of original sample data in a decision-making process. The original sample data can be expressed as $X_{m\times n} = \{x_1, x_2, \ldots, x_n\}$. Because different unit dimensions may lead to errors in the evaluation results, the original sample matrix $X_{m\times n}$ needs to be normalized to the interval [0,1]. The collapse risk evaluation indexes can be divided into positive indexes and negative indexes. For the positive index x^{+}_{ij}, the larger the value, the higher the collapse risk. The normalized value r_{ij} is determined by normalizing the positive index x^{+}_{ij} via Eq. (6).

$$r_{ij} = [x_{ij}^{+} - \min(x_j^{+})] / [\max(x_j^{+}) - \min(x_j^{+})] \tag{6}$$

When the index x^{-}_{ij} is the negative index, Eq. (7) is used to normalize the negative index x^{-}_{ij}. Where x_{ij} is the i_{th} value of the j_{th} index, the r_{ij} represents the normalized value.

$$r_{ij} = [\min(x_j^{-}) - x_{ij}^{-}] / [\max(x_j^{-}) - \min(x_j^{-})] \tag{7}$$

2.2.2 Weight calculation

After normalizing the sample data, the entropy H_i of the i_{th} index can be defined as in Eq. (8).

$$\begin{cases} H_i = -K \sum_{j=1}^{n} f_{ij} \ln f_{ij} \\ f_{ij} = r_{ij} / \sum_{j=1}^{n} r_{ij} \end{cases} \tag{8}$$

where $K = 1/\ln n$, r_{ij} is the j_{th} valid value corresponding to the i_{th} index, and m is the number of the index. Therefore, it is unnecessary to consider the case in which $f_{ij} = 0$. After determining H_i, the weight vector $e_i\,(e'_1, e'_2, \ldots, e'_n)$ of the decision indexes is obtained by Eq. (9).

$$e'_i = \frac{1 - H_i}{m - \sum_{i=1}^{m} H_i} \tag{9}$$

2.3 Fuzzy evaluation theory

The fuzzy evaluation theory was first proposed by L. Azdah, an automatic control expert who's purpose was to comprehensively evaluate a decision target by combining various influencing factors. Since then, it has been adapted and applied in many fields including agriculture, economics, and underground engineering (Lombardi *et al.* 2017, Chenari *et al.* 2018).

2.3.1 Weight calculation

The principle of fuzzy evaluation is to utilize the membership function in fuzzy mathematics to describe the amount of fuzzy information in the decision system. The decision-maker considers each index in the decision-making system to establish a single-index evaluation system. They then divide the indexes for different decision-making attributes into reasonable intervals. Finally, the membership degree of varying levels of decision-making objects is calculated. The fuzzy comprehensive evaluation method is mainly composed of the following three steps.

(1) Establish a set of decision attributes and condition attributes.

(2) Establish a single index evaluation set.

(3) Establish a weight set for decision indexes.

2.3.2 Membership of single index

Suppose there are n risk evaluation objects and each object has m evaluation factors, then the evaluation object can be expressed as an m-dimensional vector i.e., $\{x_{i1}, x_{i2}, \ldots, x_{im}\}$ where x_{ij} is the actual value. Then the target attribute can be divided into l grades and be expressed as: $\{d_1, \ldots, d_k, \ldots, d_l\}$, specified with $d_1 > d_2 > d_3 > \ldots > d_l$. To conduct a collapse risk grade assessment system of the evaluation objects, it is necessary to calculate the membership of the single indexes. If μ is defined as its membership degree, then $\mu_{ij,k} = \mu(x_{ij} \in d_k)$ indicates that the evaluation object x_{ij} belongs to the level-k (Shahriar *et al.* 2012, Yazdani-Chamzini 2014, Ghasemi *et al.* 2014). The membership calculation function used to evaluate the attributes of decision objects, is an essential part of calculating the

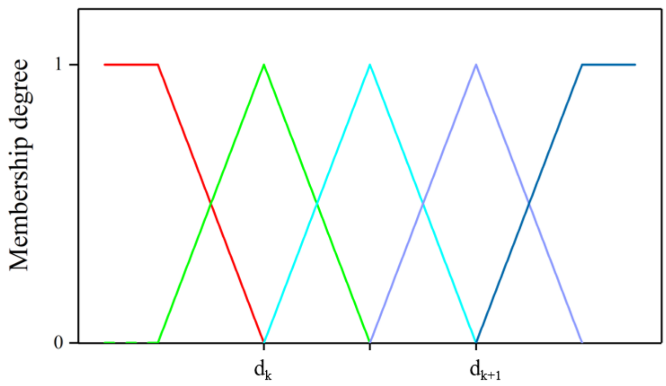

Fig. 1 Fuzzy evaluation function of the index I_k

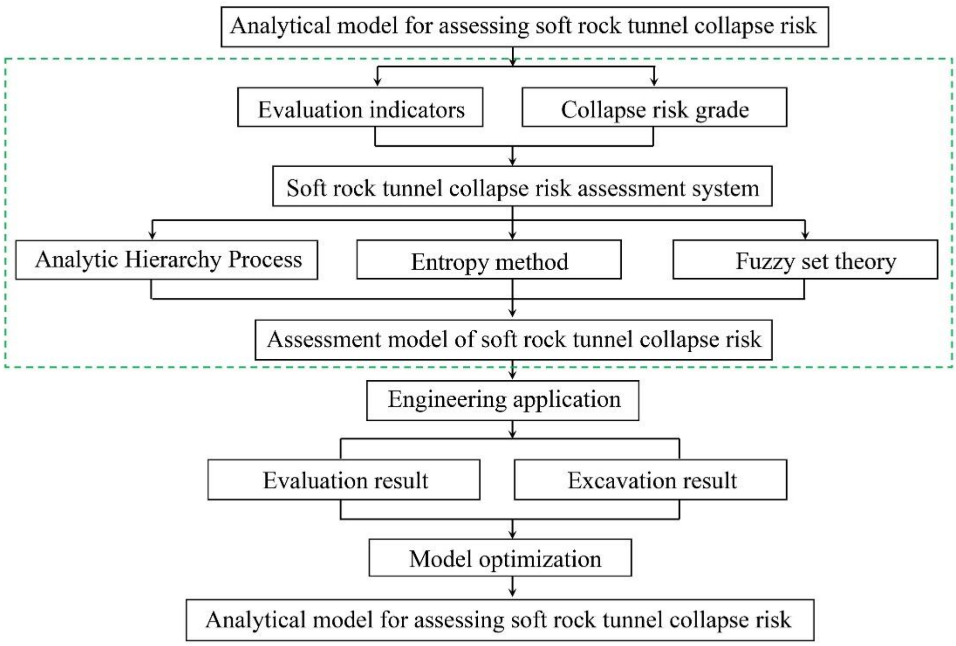

Fig. 2 Flow chart of tunnel collapse risk assessment based on fuzzy comprehensive theory

membership of the single index. Current calculation function for fuzzy analysis problems mainly include the linear, exponential, parabolic, and sinusoidal types. Because of the changing characteristics of the indexes, the triangular membership function is selected. Taking the collapse risk level-k as an example, its membership degree interval is [d_k, d_{k+1}], and the membership degree function of the i_{th} index for level-k can be expressed as in Eq. (10). The two values of d_k and d_{k+1} in Fig. 1 represent the upper and lower limits of the interval, respectively.

$$\begin{cases} \mu_i^k = \begin{cases} 0 & , d_{k+1} < \mu_{ij} \\ \dfrac{-\mu_{ij}}{d_{k+1} - d_k} + \dfrac{d_{k+1}}{d_{k+1} - d_k} & , d_k < \mu_{ij} \le d_{k+1} \end{cases} \\ \mu_{i+1}^k = \begin{cases} 0 & , \mu_{ij} \le d_k \\ \dfrac{\mu_{ij}}{d_{k+1} - d_k} - \dfrac{d_k}{d_{k+1} - d_k} & , d_k < \mu_{ij} \le d_{k+1} \end{cases} \end{cases} \tag{10}$$

The single-index evaluation matrix $\mu_{n\times m}$ in Eq. (11) of the evaluation object is obtained from the calculation of the membership degree function.

$$\mu_{n\times m} = \begin{vmatrix} \mu_{11} & \mu_{11} & \cdots & \mu_{1m} \\ \vdots & \mu_{22} & \cdots & \vdots \\ \mu_{n1} & \mu_{n2} & \cdots & \mu_{nm} \end{vmatrix} \tag{11}$$

2.3.3 Weight set

To determine the sensitivity of the index to collapse risk level, a combination of the AHP and Entropy methods are used to calculate the weight of each index. After obtaining the subjective weights e_i (e_1, e_2, …, e_n) and the objective weights e'_i (e'_1, e'_2, …, e'_n), the combination weight vector w_i (w_1, w_2, …, w_n) is established according to Eq. (12).

$$w_i = \alpha e_i + \beta e'_i \tag{12}$$

2.3.4 Fuzzy comprehensive evaluation

The comprehensive membership degree of the evaluation object is calculated according to the combination

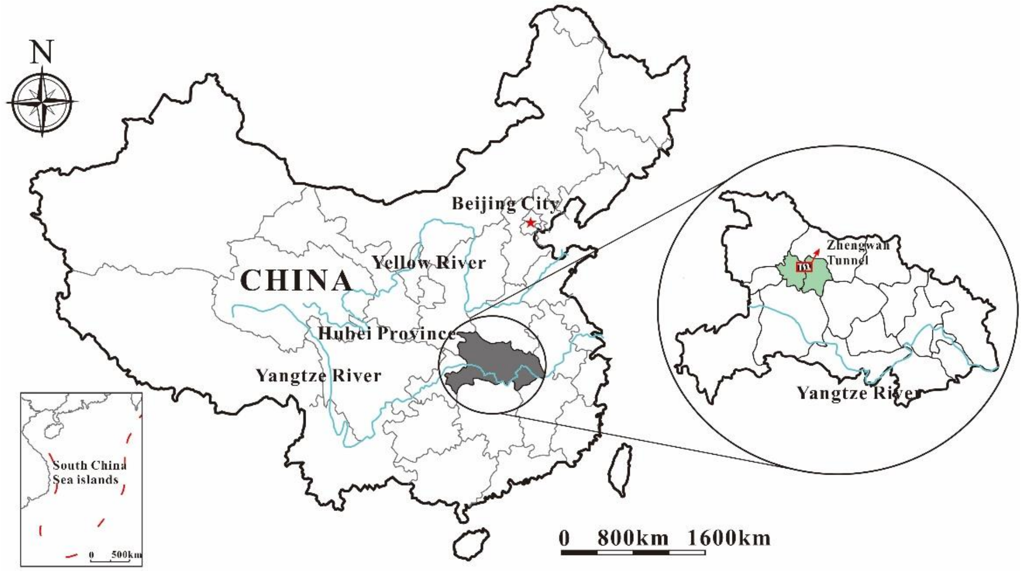

Fig. 3 The geographical location of Zhengwan tunnel

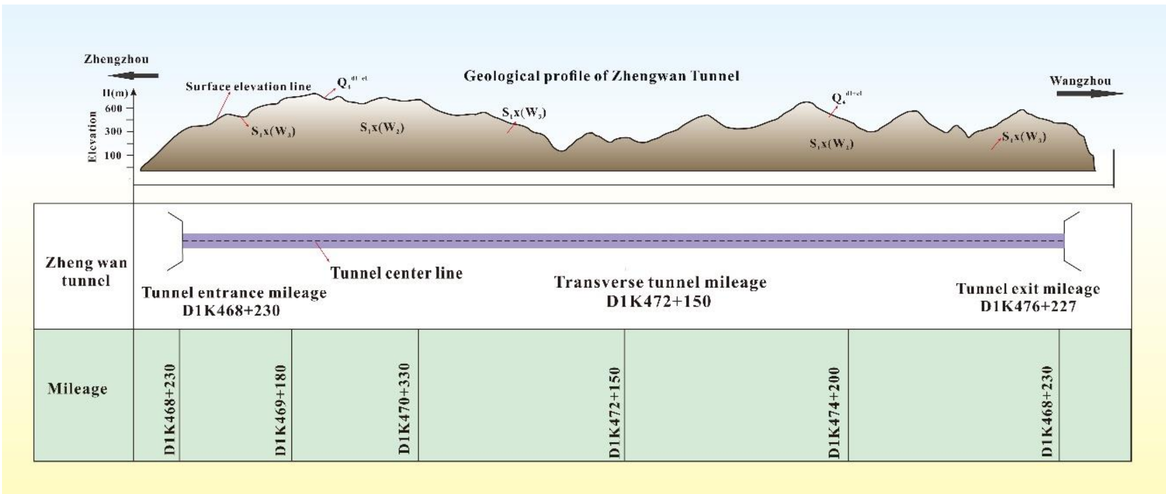

Fig. 4 The profile diagram of the tunnel

weight w_i (w_1, w_2, …, w_n) of the indexes, and the single index membership degree of the evaluation object can be seen in Eq. (13).

$$M = w \times \mu = (w_1, w_2, w_3, ..., w_n) \cdot \begin{vmatrix} \mu_{11} & \mu_{11} & \mathrm{L} & \mu_{1m} \\ \mathrm{M} & \mu_{22} & \mathrm{L} & \mathrm{M} \\ \mu_{n1} & \mu_{n2} & \mathrm{L} & \mu_{nm} \end{vmatrix} \quad (13)$$

where the matrix M is an evaluation result matrix, and μ^k_{ij} represents the multi-indexes membership degree. The final collapse risk level of the evaluation target is determined based on the principle of maximum membership. If $\mu^{\mathrm{k}}_{ij}(d_{\mathrm{i}}) = \max\{\mu^{\mathrm{t}}_{ij}(d_{\mathrm{i}}) \mid t = 1, 2, \cdots, l\}$, the level of μ^{k}_{ij} is k. Moreover, the flow chart of the investigation method is shown in Fig. 2.

3. Engineering application

3.1 Overview of the engineering

The Zhengwan high-speed railway tunnel is located in the Hubei Province of China with a total length of 7,827.27 m. The tunnel is in a tectonic erosion low mountain landform area (Fig. 2). The terrain is generally high in the middle and low on both sides. The maximum depth of the tunnel is 288.4 m, and the grades of the surrounding rocks in the construction area are mainly grade III and grade IV. (Fig. 3).

The Zhengwan high-speed railway tunnel area has unfavourable geology, including rock heaps, tunnel bias, and jointed dense zones. The main components of a rock heap are silty clay, shale gravel, and block stone. The interface angle of the rock and soil is between 14° and 62°, the rear section of the rock heap is steep, and the anterior section is slow. The rock strata of the rock heap are broken where joint fissures develop and the terrain is steep. These sections are prone to collapse under the adverse effects of weathering, self-weight, and groundwater. In construction, advanced geological prediction techniques, including TSP203 and ground-penetrating radar, is used to predict the unfavourable geology and ensure construction safety.

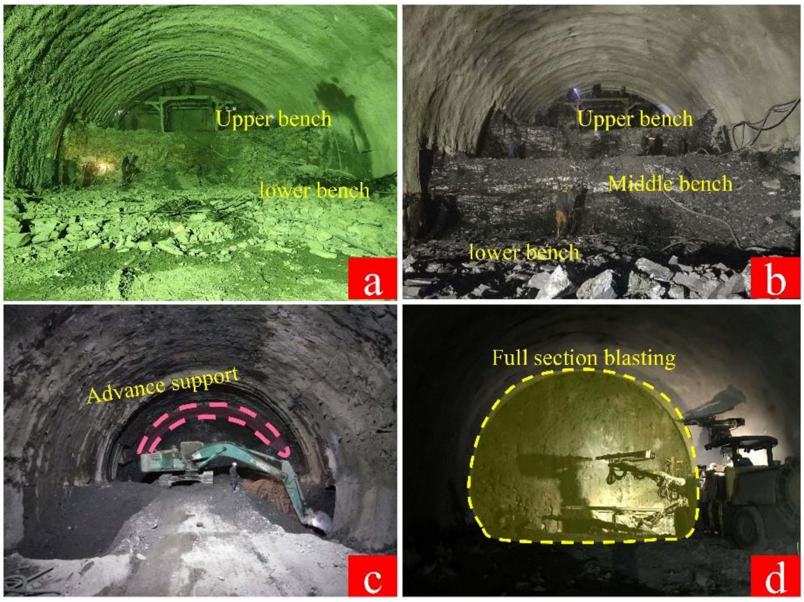

Fig. 5 (a) Two bench method, (b) Three bench method, (c) Three-bench seven-step method and (d) Full section blasting

Table 3 Quantization of construction method

Method	M_1	M_2	M_3	M_4	M_5
Quantitative range	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1.0
Value	0.2	0.4	0.6	0.8	1.0
Grades	I	II	III	IV	V

*Note: M_1-double bench method, M_2-Three bench method. M_3-Three bench seven steps method, M_4- M_3+temporary invert and M_5-CRD method

Table 4 Classification standard of support method

Risk grade	Support method				
	Steel arch spacing	Anchor number length(m)	Advanced support (m)	Grouting thickness	Standardized value
	I	II	III	IV	
I	I18,1	Φ42conduit, 40, 4.5	Φ22, 13, 3.5	C35, 25	S_1(0.2)
II	I20b,0.6	Φ42conduit 50,4	Φ22, 13, 4	C35, 28	S_2(0.4)
III	I22,0.6	Φ42conduit 50,4	Φ22, 12, 4	C35, 29	S_3(0.6)
IV	H175,0.6	Φ42conduit 50,4	Φ25, 16, 4	C35, 29	S_4(0.8)
V	H175,0.6	Section grouting	Φ25, 18, 4	C35, 29	S_5 (1)

3.2 Soft rock tunnel collapse risk evaluation index

(1) Rock mass strength I_1

The strength of tunnels' rock mass is related to the stability of surrounding rock. If the strength of the rock mass is high, the self-stability of the surrounding rock is good, and the collapse risk is low. In contrast, if the strength of the rock mass is low, the self-stability of the surrounding rock is poor, and the collapse risk is high. The uniaxial compressive strength δ_c obtained from the uniaxial compressive strength (UCS) test is selected as a quantitative index for the evaluation of rock mass strength. According to the value of the UCS, the surrounding rock is divided into five grades (Table 6).

(2) Buried depth I_2

In tunnel excavation, the rock mass above the tunnel will form a relatively stable natural arch structure within a certain range. The methods and techniques used in shallow tunnel excavation have a limited scope. For the soft rock tunnels, the deeper the buried depth of the tunnel, the worse the self-stability and the higher the collapse risk. As shown in Table 6, the buried depth h of the tunnel is divided into five grades (Wilson *et al.* 2013).

(3) Construction method I_3

Appropriate excavation methods can improve the stability of the surrounding rock to a certain extent. The most commonly used soft rock tunnel construction methods mainly including the bench method and the center cross diagram (CRD) method. The full-section method is generally adopted for tunnels with high stability. The CRD, three-bench, and three-bench seven-steps excavation methods are mainly adopted for tunnels with poor stability (Zhang *et al.* 2015). According to the degree of influence the construction has on the surrounding rock, the construction method is divided into five grades as shown in Table 3.

(4) Support method I_4

The supporting structure is an essential part of construction risk control, which can greatly increase the stability of the surrounding rock and reduce the risk of tunnel collapse. Different methods of support have different support strengths. The support strength is divided into five levels, according to different support methods (Table 4).

(5) Groundwater condition I_5

Soft rock has the characteristicsof loose, poor stability, and high porosity. Therefore, an increase in water content in the surrounding rock will lead to an increased collapse risk. Especially for soft rock tunnels with a high sensitivity to water that developed joint fissures, once the groundwater content increases, the tunnel becomes extremely prone to collapse. Therefore, groundwater condition is an essential evaluation index for tunnel collapse risk (Shrestha and

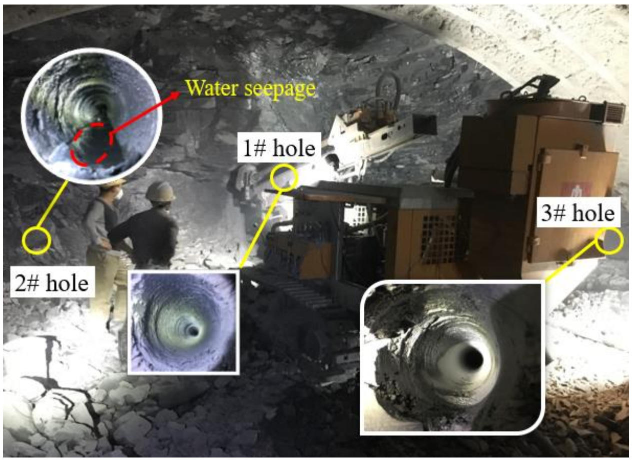

Fig. 6 Advanced horizontal drilling and groundwater condition

Table 5 Classification standard of construction level

Score	0-20	20-40	40-60	60-80	80-100
Description	lower	low	medium	high	higher
Quantitative standard	0~0.2	0.2~0.4	0.4~0.6	0.6~0.8	0.8~1.0
Level	I	II	III	IV	V

Note: Scoring criteria: a. Degree of completion of tunnel monitoring, b. Timeliness of geophysical detection and c. Construction experience of similar projects

Table 6 The collapse risk evaluation indexes and grading standards for soft rock tunnels

Index	Risk grades for the collapse of soft rock tunnels				
	Extremely high	High	Medium	Low	Micro
	I	II	III	IV	V
I_1	0~10	10~20	20~30	30~40	40~60
I_2	0~30	30~60	60~90	90~150	150~250
I_3	0.2(M_1)	0.4(M_2)	0.6(M_3)	0.8(M_4)	1.0(M_5)
I_4	0.2(S_1)	0.4(S_2)	0.6(S_3)	0.8(S_4)	1.0(S_5)
I_5	60~90	45~60	30~45	15~30	<15
I_6	0~0.2	0.2~0.4	0.4~0.6	0.6~0.8	0.8~1.0
I_7	60~80	45~60	30~45	15~30	<15
I_8	0~0.2	0.2~0.4	0.4~0.6	0.6~0.8	0.8~1.0

Note: I_1: Uniaxial compressive strength, I_2: Buried depth, I_3: Construction method, I_4: Support method, I_5: Groundwater condition; I_6, Rock mass integrity, I_7: Dip and I_8: Construction level

Panthi 2014). The amount of the groundwater per 10 m length of the tunnel is obtained by the advanced horizontal drilling (Fig. 6), is selected as a quantitative index of the groundwater condition. The groundwater condition is divided into five levels in Table 6.

(6) Rock mass integrity I_6

Rock mass integrity is a qualitative criterion for the integrity of surrounding rock. The rock mass integrity coefficient K_v is generally selected as the evaluation index

Table 7 The description of collapse risk grade of soft rock tunnels

Collapse risk grade	The description of collapse risk grade
Extremely high (I)	The collapse risk is extremely high. Partial collapse accident will occur during excavation. The volume of the collapsed surrounding rock exceeds 20 m^3.
High (II)	The collapse risk is high. The cumulative deformation of the support structure may reach 50~60 mm per day, which above the normal range. Change the construction and support method according to the buried depth and the amount of water inflow.
Medium (III)	The collapse risk is medium. The cumulative deformation of the tunnel may reach 40~50 mm per day, which within the normal range. Increase the frequency of monitoring and measurements to detect the precursors to the tunnel collapse.
Low (IV)	The collapse risk is low. The cumulative deformation of the tunnel may reach 25~40 mm per day. It is unnecessary to change the construction or support methods.
Micro (V)	The collapse risk of the tunnel is micro. The cumulative deformation of the tunnel is less than 20 mm per day. It is not necessary to change the construction or support methods.

and is determined according to Eq. (14).

$$K_v = \left(V_p / V_s\right)^2 \tag{14}$$

where V_p is the longitudinal wave velocity of the rock mass, which can be obtained by TSP203, a detection technique for advanced geological prediction. V_s is the transverse wave velocity of the rock mass, which can be obtained through laboratory tests and existing specifications. The rock mass integrity is quantitatively classified according to the rock mass integrity coefficient.

(7) Dip I_7

The attitude of strata refers to the orientation of strata formed by inclination angle, trend, and inclination in space. The bias is the inclination angle of the rock mass and can be obtained from the geological sketch. For soft rock bias tunnels, the dip of the rock mass has a greater impact on the stability of the rock mass (Bakun-Mazor *et al.* 2009, Cui *et al.* 2014). The dip of rock strata is divided into five grades in Table 6.

(8) Construction level I_8

The quality of the tunnel is inseparable from the level of construction on-site. The level of construction mainly includes the level of on-site management, the degree to which the work is monitored, and the timeliness of the advanced forecasting work. A higher level of construction equates to higher productivity. The classification standard for the levels of construction can be seen in Table 5.

The daily construction evaluation score is taken as the evaluation standard of the level of construction, and the level of construction is quantitatively classified, as seen in Table 5. Above all, the grading standard for the collapse risk evaluation index is listed in Table 6, i.e., extremely high (I), high (II), medium (III), low (IV), and micro (V), respectively.

Correspondingly, the grading standards of the evaluation indexes were divided into five grades, which constituted

Table 8 Sample data for evaluation indexes

No.	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
1	32	15	0.2	0.2	16.59	0.228	44	0.6
2	32	29.5	0.4	0.4	6.85	0.413	66	0.6
3	30	40	0.4	0.4	8.23	0.329	64	0.6
4	30	48.5	0.4	0.6	7.39	0.558	60	0.8
5	37	52	0.6	0.6	22.5	0.467	54	0.8
6	28	67	0.6	0.6	21.8	0.322	47	0.6
7	28.5	75.5	0.6	0.6	36.4	0.355	45	0.8
8	25	83.8	0.6	0.6	25.8	0.314	48	0.4
9	25	88.5	0.6	0.6	17.5	0.651	52	0.4
10	27	91.9	0.6	0.6	36.4	0.675	63	0.8
11	27.6	94.5	0.8	1.0	9.8	0.538	86	0.8
12	25.5	101.5	0.8	1.0	11.8	0.421	80	0.8
13	25.5	114.5	0.8	1.0	12	0.635	85	0.8
14	25.5	127	0.6	0.6	10.44	0.667	83	0.2
15	33	133.5	0.6	0.6	21.6	0.421	66	0.8
16	32.6	141	0.6	0.6	22	0.285	78	0.2
17	32.6	149	0.6	0.6	20.5	0.713	74	0.8
18	32.5	154	0.8	0.8	23.3	0.788	54	0.8
19	36	158	0.8	0.8	27.5	0.843	59	0.6
20	36	163	0.8	0.8	33.6	0.835	62	0.6
21	31.9	166	0.8	0.8	25.3	0.821	58	0.8
22	31.9	174.5	0.6	0.6	40.8	0.725	55	0.6
23	34	180.6	0.6	0.6	42.3	0.357	49	0.6
24	34	184.8	0.6	0.6	41.5	0.388	47	0.2
25	33	195.7	0.8	1.0	28.8	0.475	56	0.8
26	33	199.5	0.8	1.0	25.5	0.552	57	0.6
27	30	204.6	0.6	1.0	16.7	0.468	63	0.8
28	30	211.5	0.6	1.0	12.5	0.675	60	0.2
29	27.6	226.5	0.8	1.0	12.8	0.731	60	0.6
30	27.6	235.5	0.8	1.0	10.9	0.648	55	0.6

the grading standards (Table 6). Moreover, the description of different collapse risk grades and the suggested construction plan are listed in Table 7.

3.3 Engineering application

The soft rock tunnel collapse risk evaluation model was used for evaluating the collapse risk of the Zhengwan tunnel. In Table 8, the data from 30 sections of the Zhengwan Tunnel were selected as the data samples for weight calculation and collapse risk evaluation model establishment.

3.3.1 Weight calculation

Based on Eqs. (1)-(5), the order of the importance of collapse risk assessment indexes are listed in Table 9. The calculation results showed that the consistency test coefficient $CR = 0.0117 < 0.1$. According to the principle of

Table 9 Order of importance of collapse risk assessment indexes

Index	I_1	I_4	I_5	I_6	I_7	I_2	I_3	I_8	Weight
I_1	1	1	2	3	3	4	5	5	0.252
I_4	1	1	2	3	3	4	5	5	0.252
I_5	1/2	1/2	1	2	2	3	4	4	0.160
I_6	1/3	1/3	1/2	1	1	2	3	3	0.099
I_7	1/3	1/3	1/2	1	1	2	3	3	0.099
I_2	1/4	1/4	1/3	1/2	1/2	1	2	2	0.062
I_3	1/5	1/5	1/4	1/3	1/3	1/2	1	1	0.038
I_8	1/5	1/5	1/4	1/3	1/3	1/2	1	1	0.038

Note: RI=1.4100, CI=0.0164, CR=0.0117<0.1

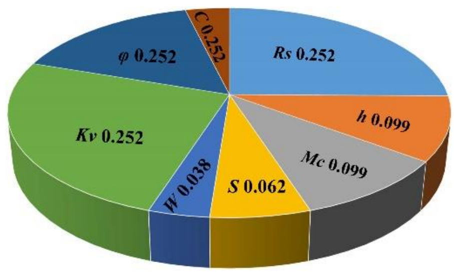

Fig 7 Subjective weight

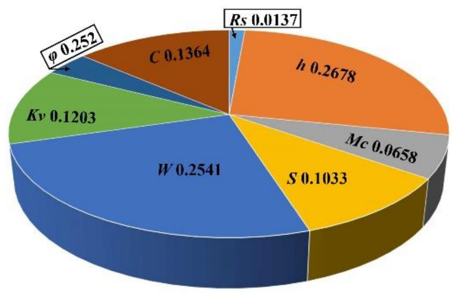

Fig 8 Objective weight

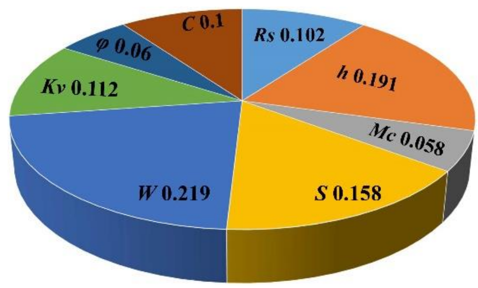

Fig 9 Combination weight

Table 10 Objective weights

Index	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
H_i	1.00	0.172	-0.050	-0.118	0.427	0.061	-0.274	0.081
Weight	0.0137	0.2678	0.0658	0.1033	0.2541	0.1203	0.0386	0.1364

Note: H_i represented the entropy and was obtained from Eq.(8)

the analytic hierarchy process method, the importance ranking process meets the consistency requirements. The

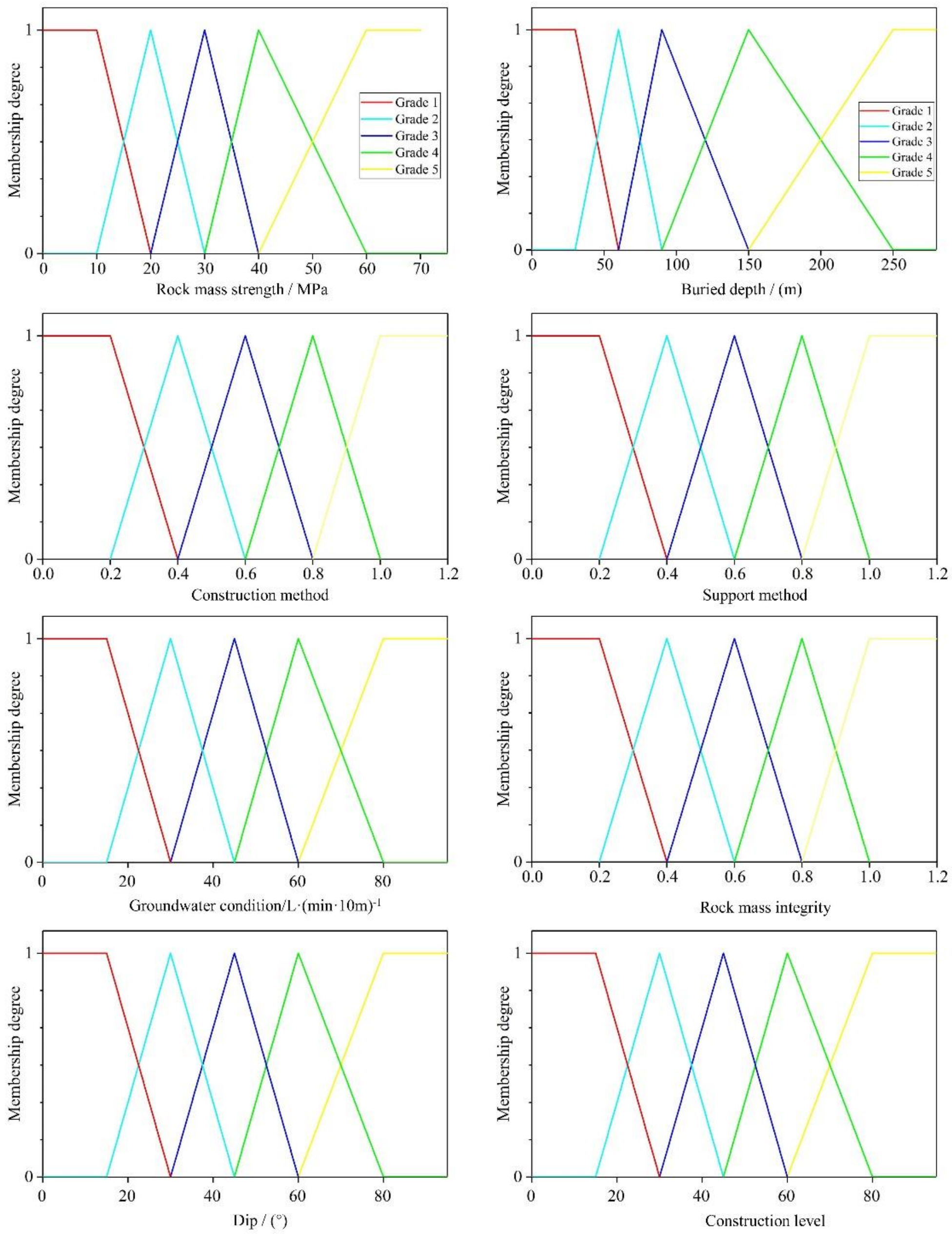

Fig. 10 Membership function of collapse risk assessment indexes for soft rock tunnel

subjective weights obtained by the analytic hierarchy process method are shown in Fig. 7.

The objective weights of each evaluation index were obtained via Eqs. (6)-(9). The results can be seen in Table 10 and Fig. 8.

To reasonably distribute the subjective and objective weights, the weight distance function $f(e_i', e)$ is introduced to calculate the distribution coefficients of the two results.

$$\begin{cases} f(e_i', e) = \left[\dfrac{1}{2}\sum_{i=1}^{n}(e_i' - e_i)^2\right] \\ \alpha + \beta = 1 \\ (\alpha - \beta)^2 = \dfrac{1}{2}\sum_{i=1}^{n}(e_i' - e_i)^2 \end{cases} \tag{15}$$

weight distribution coefficients obtained via Eq. (15) are 0.36955 (AHP method) and 0.63045 (Entropy method). The combined weight results are shown in Fig. 9.

3.3.2 Single index membership function

For this research, the triangular membership function was selected to determine the single index evaluation matrix. If $\mu(x_{ij})$ is called the membership degree of the i_{th} index, then $\mu^k_{ij} = \mu(x_{ij} \in d_k)$ indicates that the evaluation object belongs to collapse risk level-*k*. Moreover, the membership function should satisfy the following conditions:

(1) $0 \le \mu(x_{ij} \in d_k) \le 1$;

(2) $\mu(x_{ij} \in d_k) = 1$;

(3) $\mu(x_{ij} \in U_d) = \Sigma\mu(x_{ij} \in d_k)$.

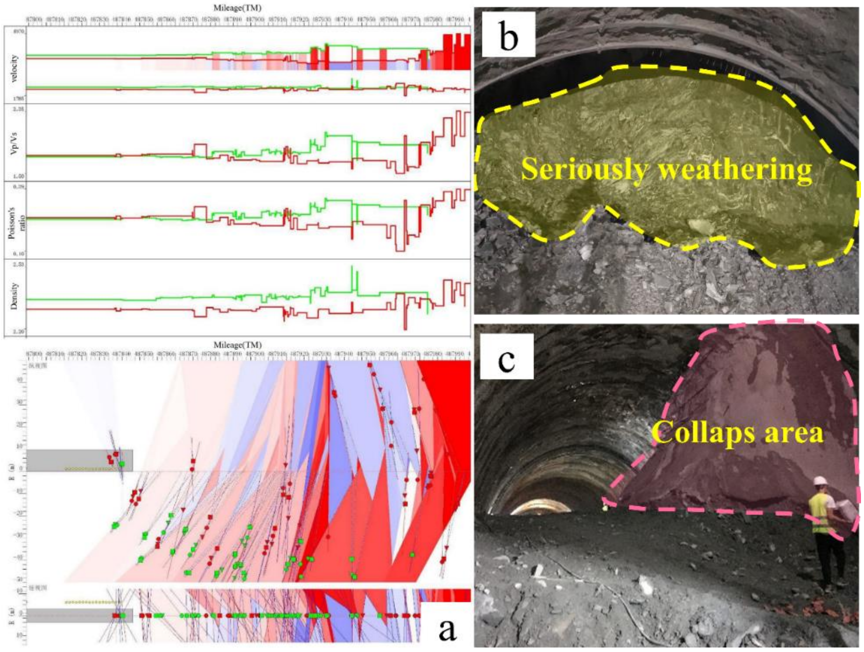

Fig. 11 (a) Petrophysical properties obtained by TSP203, (b) Excavation of the tunnel face and (c) Collapse in the tunnel

Table 11 Actual excavation situations of the tunnel construction

Section	Actual situations of tunnel excavation
1	The cumulative deformation of the supporting structure in the actual construction process reached to 45 mm/d. The collapse risk is high,
2	The collapse risk is extremely high. The vault of the tunnel partially collapsed during construction.
3	The evaluation result predicted low risk after changing the construction method. The collapse risk is medium.
4	The cumulative deformation of the supporting structure is 38 mm/d, which is beyond the normal range. The collapse risk is micro.
5	The cumulative deformation of the supporting structure is 32.5 mm/d. The collapse risk is high.

Taking level-k collapse risk as an example, its membership degree interval is $[d_k, d_{k+1}]$, and the membership degree function of the i_{th} index to level-k can be expressed as μ^k_i in Eq. (16). The single-index membership function of the collapse risk of the soft rock tunnel is established.

$$\begin{cases} \mu_i^k = \begin{cases} 0 & , d_{k+1} < \mu_{ij} \\ \dfrac{-\mu_{ij}}{d_{k+1}-d_k} + \dfrac{d_{k+1}}{d_{k+1}-d_k} & , d_k < \mu_{ij} \le d_{k+1} \end{cases} \\ \mu_{i+1}^k = \begin{cases} 0 & , \mu_{ij} \le d_k \\ \dfrac{\mu_{ij}}{d_{k+1}-d_k} - \dfrac{d_k}{d_{k+1}-d_k} & , d_k < \mu_{ij} \le d_{k+1} \end{cases} \end{cases} \tag{16}$$

The membership function μ_{I1} of the index I_1 under different collapse risk levels are calculated in Eqs. (17)-(21) (Fig. 10).

$$\mu_{I_1}{}^{\mathrm{I}}(x) = \begin{cases} 1 & x \le 10 \\ \dfrac{20-x}{20-10} & 10 < x \le 20 \\ 0 & x > 20 \end{cases} \tag{17}$$

$$\mu_{I_1}{}^{\mathrm{II}}(x) = \begin{cases} 0 & x \le 10 \\ \dfrac{x-10}{20-10} & 10 < x \le 20 \\ \dfrac{30-x}{30-20} & 20 < x \le 30 \\ 0 & x > 30 \end{cases} \tag{18}$$

$$\mu_{I_1}{}^{\mathrm{III}}(x) = \begin{cases} 0 & x \le 20 \\ \dfrac{x-20}{30-20} & 20 < x \le 30 \\ \dfrac{40-x}{40-30} & 30 < x \le 40 \\ 0 & x > 40 \end{cases} \tag{19}$$

$$\mu_{I_1}{}^{\mathrm{IV}}(x) = \begin{cases} 0 & x \le 30 \\ \dfrac{x-30}{40-30} & 30 < x \le 40 \\ \dfrac{60-x}{60-40} & 40 < x \le 60 \\ 0 & x > 60 \end{cases} \tag{20}$$

$$\mu_{I_1}{}^{\mathrm{V}}(x) = \begin{cases} 0 & x \le 40 \\ \dfrac{x-60}{60-40} & 40 < x \le 60 \\ 1 & x > 60 \end{cases} \tag{21}$$

To obtain the weight set w_i (w_1, w_2, …, w_n) and the single index membership degree matrix $\mu^k{}_{Ii}(x_{ij})$, the comprehensive index membership degree is calculated according to Eq. (22).

$$M = w \times \mu = (w_1, w_2, w_3, \ldots, w_n) \cdot \begin{vmatrix} \mu_{11}^{\mathrm{I}} & \mu_{11}^{\mathrm{I}} & \cdots & \mu_{1m}^{\mathrm{I}} \\ \cdots & \mu_{22}^{2} & \cdots & \cdots \\ \mu_{n1}^{t} & \mu_{n2}^{t} & \cdots & \mu_{nm}^{t} \end{vmatrix} \tag{22}$$

where μ^{k}_{ij} is called the collapse risk membership degree, the matrix $M_{1\times n}$ is the multi-index integrated fuzzy assessment matrix. The final collapse risk level is determined according to the maximum membership, i.e., if $\mu^{k}_{ij}(d_i) = \max\{\mu^{t}_{ij}(d_i)|t = \mathrm{I, II, III}, \cdots, l\}$, then the collapse risk grade of μ^{k}_{ij} (the i_{th} evaluation target) is k.

As mentioned above, the complexity of the soft rock tunnel collapse's reasons determines the diversity of the investigation methods. Based on calculating the risk of the tunnel collapse, the feasibility of the fuzzy evaluation model should be verified by comparing the evaluation results obtained from different investigating methods. The technique for order preference by similarity to an ideal solution, also known as TOPSIS, is a multi-objective decision-making method. The TOPSIS method evaluates the target according to the established decision system, which is very similar to the fuzzy theory. It mainly includes the following five steps:

a. Establish the evaluation system for soft rock tunnel collapse risk.

b. Determine the ideal and anti-ideal points.

c. Obtain the data samples of the soft rock tunnel collapse risk indexes through engineering application.

d. Calculate the ideal point grade closeness degree of each sample.

e. Obtain the evaluation results according to the evaluation system for soft rock tunnel collapse risk.

Advanced geological prediction, which can detect the unfavourable geology and reduce the collapse risk of the tunnel, is an essential part of transportation construction. As shown in Fig.11(a), the velocity ratio of the vertical and horizontal waves in this section increases sharply in a small range and then decreases rapidly. According to the interpretation principle of TSP203 that the surrounding rock strength of this section is low and the integrity is poor. The Poisson's ratio in this section suddenly decreases, which indicates that the density of the medium transmits the sound wave in this section decreases, and local fragmentation of the rock mass or water seepage may occur. Moreover, it was showed that section-1, section-4, and section-5 have lower surrounding rock grades, dense joints, and high groundwater content through advanced geological prediction techniques and geological survey data, which indicate a high collapse risk in excavation. To control the geological disaster in advance, these five sections are selected as the research object. The field data of the following five sections were obtained and are presented in Table 11.

The collapse risk grade membership degree set μ_k (μ_{I}, μ_{II}, μ_{III}, μ_{IV}, μ_{V}) of each tunnel sections to be evaluated for the tunnel sections can be obtained from the single index membership function. Taking section-1 as an example, its membership evaluation matrix can be calculated according to Eqs. (17)-(21). Thus, the membership results of section-1 are listed in Eq. (23). According to the fuzzy comprehensive theory and the Topsis method, the evaluation results of collapse risk grade are shown in Table 11. According to the characteristics of the TOPSIS method, the evaluation results obtained via the TOPSIS method are compared with those obtained by the fuzzy evaluation model.

$$\mu_{Ii}{}^{k}(x_{ij}) = \left\{\begin{array}{ccccc|l|l} 0 & 0.25 & 0.75 & 0 & 0 & \text{Rock mass strength} & 25.1 \\ 1 & 0 & 0 & 0 & 0 & \text{Buried depth} & 85 \\ 1 & 0 & 0 & 0 & 0 & \text{Construction method} & 0.3 \\ 0 & 0.06 & 0.94 & 0 & 0 & \text{Support method} & 1.83 \\ 0 & 0 & 0 & 0.6733 & 0.3267 & \text{Groundwater condition} & 12.55 \\ 0 & 0.345 & 0.655 & 0 & 0 & \text{Rock mass integrity} & 0.42 \\ 0.85 & 0.15 & 0 & 0 & 0 & \text{Dip} & 67 \\ 0 & 0 & 1 & 0 & 0 & \text{Construction level} & 0.7 \end{array}\right\} \tag{23}$$

Table 11 shows that the fuzzy evaluation results are basically consistent with the actual excavation situation. Comparing the evaluation results with the TOPSIS method and the fuzzy evaluation method, it is found that the TOPSIS method does not provide an accurate collapse risk evaluation for the tunnel with high collapse risk. Based on the field monitoring records, the five sections' excavation situations are described in Table 11. Among the three evaluation methods, section-2 has the highest collapse risk grade.

According to the geological description from the Tunnel Seismic Prediction technology, the rock mass has poor integrity (Fig 11(a)). It can be seen in the sketch of the tunnel face that the rock mass of section-2 has a large dip, and the weathering degree of the rock around the tunnel face is severe (Fig 11(b)). The field record for the advanced horizontal drilling shows that the amount of water inflow in this section is 16.8 L/ (min*10 m).

The design of the section-2 has a higher grade of surrounding rock, and the support method is S_2. The surrounding rock grade of section-2 has changed during construction. The surrounding rocks' stability of section-2 becomes worse during construction, but the construction plan was not adjusted in time. The vault of the tunnel partially collapsed during construction, see Fig 11c. The prediction results of collapse risk indicate section-4 has a high collapse risk. The design parameters of section-4 indicate that the excavation method of this section had a large influence on the stability of the surrounding rock, and the strength of the supporting structure was not adequate. Before construction, the construction plan for this section was adjusted. Due to the advanced optimization of the construction scheme, the collapse risk evaluation result of section-4 has been reduced to a low collapse risk, i.e., grade IV (see Table 11). The deformation of the supporting structure was small, and the deformation rate was 25 mm/d during excavation, which is within the normal range for tunnel deformation.

4. Discussion

In selecting the investigation method of evaluating soft rock tunnel collapse risk, the research status and engineering background characteristics are considered comprehensively. Probabilistic analysis and machine learning have a high requirement for sample data diversity and a long calculation cycle. In contrast, the fuzzy set theory is more suitable for dynamic analysis and study of collapse risk of soft rock tunnel. Moreover, the engineering application in this paper also verified that the fuzzy comprehensive model could accurately evaluate the collapse risk grade of soft rock tunnel.

Since in selecting the stability evaluation index of the excavation face, the indexes are required to be universal and easy to obtain. In this paper, the groundwater in liters per minute per 10 m length of the tunnel measured by the advanced horizontal drilling machine is selected as the quantitative index of groundwater condition rather than the groundwater information obtained from the geophysical prospecting instruments. Moreover, different types of projects may have different construction and support methods. Based on applying the fuzzy evaluation model, the reliability of the selected indexes should be further investigated to optimize the evaluation model.

The purpose of weight calculation is to judge the importance of the evaluation index by quantitative analysis. Through analyzing the advantages of subjective and objective weight calculation methods, the analytic hierarchy process and entropy method were combined to calculate the subjective and objective weights of the collapse risk evaluation indexes in this paper. Since the strength of the surrounding rock of the soft rock tunnel is generally low, the degree of variation in surrounding rock integrity is small, which leads to the low objective weight of the surrounding rock integrity. The calculation result shows that the weights of the groundwater conditions and surrounding rock integrity are quite different. The result shows a significant difference between the subjective weight and the objective weight, which indicates the importance of using the combined weight methods to obtain the weights of the evaluation indexes.

The construction monitoring results indicated that, given unfavorable geological features and inappropriate construction methods, soft rock tunnels might deform abnormally, which may lead to the tunnel collapse. Therefore, the tunnel's deformation parameters can be regarded as the most intuitive predictive information for predicting tunnel collapse. In the process of the tunnel structure deformation tends to be stable, the values of groundwater parameters, surrounding rock integrity, and other collapse risk evaluation indexes may change, which may lead to the inconsistency between the evaluation results of tunnel collapse risk and reality. Thus, the tunnel deformation parameter is taken as one of the classification standards of the collapse risk grade of on-site excavation.

5. Conclusions

The collapse risk of soft rock tunnel is influenced by qualitative and quantitative indexes. This paper uses the fuzzy comprehensive evaluation theory to establish the quantitative criteria of the collapse risk decision index, and makes scientific and reasonable evaluation of the fuzzy information between variables. The following conclusions are drawn.

Based on a comprehensive analysis of collapse accidents and research status globally, the following eight tunnel collapse risk evaluation indexes were selected: rock mass strength, tunnel depth, support strength, dip angle, groundwater condition, rock integrity, excavation method and construction level. The weight of each index was calculated by the analytic hierarchy process method and entropy method. The distance function method is used to allocate the subjective and objective weights. The final calculation results indicate that the groundwater condition has the highest weight, while the tunnel's dip angle has the lowest weight. The result also indicates that it is essential to use the comprehensive weight method to calculate the weight of the index.

This paper selected five sections for collapse risk evaluation in the engineering application part. Moreover, the collapse risk evaluation results of the fuzzy comprehensive model under different conditions are compared with those obtained from the TOPSIS method. The evaluation results indicated that the collapse risk of section-1 is grade I and has an extremely high collapse risk. During excavation, a partial collapse occurred in section-1. The collapse risk of section-2 is grade II, which has a high collapse risk. After changing the construction and the support methods, the re-evaluated result of section-2 was grade IV, which indicates a low collapse risk and is consistent with the actual excavation situation. The comparison between the fuzzy comprehensive evaluation model and the TOPSIS method shows that the evaluation results of the TOPSIS method are not consistent with the actual excavation situation. Generally speaking, the fuzzy comprehensive evaluation method can accurately predict the tunnel collapse risk and verify the optimization effect of the construction.

The tunnel deformation data and construction parameters involved in this research are obtained from on-site construction monitoring. In evaluating the collapse risk of the soft rock tunnel, the collapse risk level is classified into five grades according to the cumulative deformation of the tunnel support structure. The application effect of the model in the Zhengwan tunnel also verifies the feasibility of this classification method. Since the data used in this research are all from the Zhengwan tunnel, the research results inevitably have some regional characteristics. The improvement of the database and the optimization of model operation capability will be realized by applying the evaluation model to more engineering.

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