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# A TBM tunnel collapse risk prediction model based on AHP and normal cloud model

Peng Wang, Yiguo Xue, Maoxin Su*, Daohong Qiu and Guangkun Li

*Geotechnical and Structural Engineering Research Center, Shandong University, Ji'nan, Shandong, China*

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**Abstract.** TBM is widely used in the construction of various underground projects in the current world, and has the unique advantages that cannot be compared with traditional excavation methods. However, due to the high cost of TBM, the damage is even greater when geological disasters such as collapse occur during excavation. At present, there is still a shortage of research on various types of risk prediction of TBM tunnel, and accurate and reliable risk prediction model is an important theoretical basis for timely risk avoidance during construction. In this paper, a prediction model is proposed to evaluate the risk level of tunnel collapse by establishing a reasonable risk index system, using analytic hierarchy process to determine the index weight, and using the normal cloud model theory. At the same time, the traditional analytic hierarchy process is improved and optimized to ensure the objectivity of the weight values of the indicators in the prediction process, and the qualitative indicators are quantified so that they can directly participate in the process of risk prediction calculation. Through the practical engineering application, the feasibility and accuracy of the method are verified, and further optimization can be analyzed and discussed.

**Keywords:** analytic hierarchy process; collapse risk; normal cloud model; prediction model; TBM tunnel

## 1. Introduction

The Tunnel Boring Machine (TBM) construction method is increasingly used in tunnel engineering and underground engineering. Compared with traditional excavation methods such as the drill-blasting method, TBM has the advantages of fast digging speed, a high degree of automation and non-interference between different processes. After more than a hundred years of development, there are now open-type, shield-type and multi-shield types and other different forms of TBM can adapt to different types of engineering geological conditions. At present, TBM has become an important method in the construction of the mountain tunnel, submarine tunnel and water supply tunnel.

Although there is still a shortage of research on adverse geological hazards in the TBM tunnel, some progress has been made. For example, in terms of groundwater, Font-Capó *et al.* (2011) consider the unexpected high-water inflows to be a major threat to the safety of tunnel construction, and propose to accurately predict the water table and tunnel seepage by establishing a quasi-3D numerical model with a moving tunnel face boundary condition to avoid geological disasters such as water inrush. Adoko *et al.* (2017) propose a method of using Bayesian inference and using the Deviation Information Criterion (DIC) to predict the permeability of the TBM tunnel surrounding rock. In the aspect of rock blasting disaster. Gong *et al.* (2012) propose a method to predict the rock burst disaster in the TBM tunnel by using a true three-axis experiment that can simulate the rock blasting process under different ground stress conditions. In the detection of large-scale unfavorable geological bodies, Li *et al.* (2018) propose that it can be detected by a reasonable advance prediction method (such as three-dimensional induced polarization method, earthquake advanced geological prediction method, etc.) for the problem of poor adaptability of TBM construction when crossing variable strata, and then accurate prediction of bad geology such as caves, faults and fracture zones. In addition, as computing software continues to enrich and improve, more and more numerical simulation methods are being used in research related to TBM tunnels. For example, in terms of disc cutter erosion and wear, Haeri *et al.* (2014) use a higher-order semi-infinite displacement discontinuity method to analyze the stress of the rock mass in front of the roller and establish a special crack tip element to numerically simulate the eroded disc cutter. Tan *et al.* (2017) analyzed the relationship between the movement law and the wear amount of cutter head in the process of rock breaking by hobs and established a wear prediction model of disc cutter.

Collapse is a major threat to the construction of the tunnel (as shown in Fig. 1). Because the TBM tunnel is constructed with a full-section digger and the internal structure is complex, compared to the tunnel constructed by drilling and blasting, the damage in the TBM tunnel caused by the collapse is even greater, and recovery efforts are more difficult (Lee *et al.* 2019). Therefore, according to the actual situation of the project, it is more important to use scientific and effective methods to make predictions and provide theoretical guidance to construction workers in the TBM tunnel. TBM tunnel collapse can be divided into a variety of types, such as according to the location of the

*Corresponding author, Ph.D.
E-mail: sumaoxin2008@163.com

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Fig. 1 TBM tunnel collapse

collapse, it can be divided into cave entrance collapse and inside collapse. The former according to the collapse in the tunnel cross-section of the position can be further divided into the cave roof collapse, sidewall collapse and palm surface collapse, wherein the collapse of the palm surface may cause the TBM discs to be stuck and cannot continue to dig in, resulting in construction obstruction and equipment damage. No matter what kind of collapse occurs, it will lead to the construction to be blocked and endanger the construction personnel's safety.

At present, the research on the risk of TBM tunnel collapse is still very lacking, and the TBM tunnel collapse will cause great harm to the project. In addition to the damage inherent in the traditional tunnel collapse, but also cause TBM failure, jamming and even scrap, bring huge economic losses. Therefore, it is of great significance to establish an accurate and reliable risk prediction model of TBM tunnel collapse to improve the safety of its construction and ensure the efficiency of construction. This paper refers to the traditional tunnel collapse risk prediction model (Zhang *et al.* 2016, Xue *et al.* 2018, Su *et al.* 2019) and the related research of various geological disasters in the TBM tunnel, combines with the engineering characteristics of TBM tunnel, establishes a TBM tunnel collapse risk level prediction model based on analytic hierarchy process (Dikmen and Birgonul 2006) and normal cloud model (Li and Yang 2018). First of all, by collecting relevant engineering data, analogy similar engineering examples, identify all risk factors that may cause collapse in a tunnel segment. After a preliminary analysis, the risk indicator system used to predict the model calculation and the values of each indicator can be determined. For qualitative indicators that cannot be directly assigned, it can be quantified or equivalent to relevant quantitative indicators by appropriate methods. Secondly, according to the actual engineering, the range of values of each risk indicator in the tunnel segment to be evaluated can be determined, and it can be divided into five parts according to the order of high to low-risk level, corresponding to five risk levels. Thirdly, the objective weight of the indicators in the indicator system can be determined by the improved analytic hierarchy process. Finally, a normal cloud model can be established and the indicator system can be brought in to predict the risk level of collapse in the tunnel segment to be evaluated. In order to verify the accuracy and feasibility of this method, the prediction results should be compared with the actual excavation results. Where the actual results are not met, the reasons should be analyzed and improved so that the prediction model can be continuously improved.

## 2. Methods

The stability evaluation process of tunnel involves many parameters, which are related to the mechanical properties of tunnel surrounding rock and are important factors for analyzing the risk of tunnel collapse, deformation and other disasters (Fraldi *et al.* 2019). Statistics show that there are many factors that cause tunnel collapse under different geological conditions. For example, in the mountain tunnel under the drilling and blasting method, the risk factors for collapse include 25 items such as tunnel depth, cross-sectional span and groundwater conditions. Considering the particularity of the construction mode of TBM, the characteristics of the TBM method should be fully considered in the collapse risk prediction of certain type tunnels (mountain tunnels, undersea tunnels, water supply tunnels, etc.), and be fully reflected in the process of selecting risk indicators. In this paper, a TBM tunnel is used as an example to explain a risk classification and prediction method of TBM tunnel collapse.

### *2.1 TBM tunnel collapse ındicators selection*

In the mountain tunnel, the surrounding rock grade and groundwater condition are common indicators that reflect the geological and hydrogeological conditions of tunnel engineering. From the perspective of rock mass mechanics, on the one hand, the integrity of rock mass is an important indicator affecting the stability of tunnel surrounding rock, which can be quantitatively analyzed by elastic wave velocity test. In practical engineering, the grade of surrounding rock determined according to the strength and integrity of surrounding rock and the influencing factors such as in-situ stress is an important basis for tunnel design and construction. The essence of tunnel collapse is the instability of surrounding rock. Therefore, when analyzing the risk of collapse, the grade of surrounding rock should be included in the indicator system. The higher the surrounding rock level, the better the overall nature of the rock body, the lower the hidden danger of the collapse. On the other hand, groundwater is the main factor leading to rock softening. The softening of rock mass will significantly reduce its strength, affect the mechanical properties of tunnel surrounding rock, and increase the risk of collapse. Therefore, groundwater conditions also need to be used as an important indicator to analyze the risk of tunnel collapse. Groundwater conditions including water level height, cave, underground dark river and other water development. Poor groundwater conditions indicate that the surrounding rock by groundwater erosion, softening, dissolving and other effects, the strength of the surrounding rock decreased, the risk of collapse increased (Reilly 2000, Choi *et al.* 2004).

Tunnel depth and span are important indicators to characterize tunnel design characteristics. Loosening pressure and deformation pressure are two important surrounding rock pressures. According to Terzaghi's surrounding rock pressure calculation formula, Protodyakonov's mountain rock pressure theory and Finner's deformation pressure calculation formula, the buried depth and span of the tunnel are important factors affecting the surrounding rock pressure. In general, tunnels with larger buried depths and smaller spans are more stable and the risk of collapse is lower. Therefore, these two items should be used as evaluation indicators when conducting tunnel collapse risk analysis. Since the TBM tunnel span is the diameter of the cutter head, the tunnel span is represented by the diameter of the TBM cutter head.

In the drilling and blasting tunnel, the surrounding rock condition is an important factor that affects the efficiency and safety of excavation. In contrast, in TBM tunnels, not only the surrounding rock conditions but also the mechanical parameters and rock mechanism relations of TBM should be considered. To do this, the field penetration index *FPI* can be introduced as a risk indicator, quantifying the ease of digging in TBM tunnels, where, $FPI=F_n/p$, $F_n$ is single-disc thrust (kN), $p$ is rotational speed (mm/rev). By definition, the *FPI* represents the hob thrust required for the depth of the rock unit, stripping off the influence of non-geological parameters such as the diameter and speed of the plate, which can be used as a measure of the easy-to-dig of the rock. The higher the *FPI* value, the greater the thrust required to produce the same depth, indicating that the more difficult it is for the rock body to dig in.

The above several are common indicators in the mountain TBM tunnel, and the final risk indicators system should be determined in the case of the tunnel's design characteristics, geological conditions, etc. when the collapse risk prediction is carried out on a particular TBM tunnel. In addition, among the indicators, the indicator values (such as buried depth, span, etc.) can be directly determined as quantitative indicators, and those that cannot directly determine the indicator values are called qualitative indicators (such as groundwater conditions). The latter needs to be assigned before it is applied to the risk prediction system.

### 2.2 TBM tunnel collapse ındicator weight calculation

The determination of the indicator's weight is an important part of the risk prediction system. The objective and accurate index weight is the basis of the accuracy and reliability of risk prediction results. Compared with other traditional tunneling methods, the TBM tunneling method has a relatively small number of tunnels, and the statistical data of the collapse cases of TBM tunnels are relatively scarce because of its late appearance, high cost and high requirements for geological conditions. The commonly used objective weight algorithm usually needs a large number of relevant statistical data as the basis, and it is difficult to directly apply to the TBM collapse risk prediction system.

In the 1970s, Saaty, an American operations physicist, proposed the famous Analytic Hierarchy Process (AHP), which is to break down the elements related to decision-making into goals, guidelines, scenarios, and so on. And on this basis, qualitative and quantitative analysis of the decision-making methods. This method considers the weight comparison relationship of any two indicators within the indicator system and has the advantages of system, flexibility, and simplicity (Xue *et al.* 2019). Considering the data of the TBM tunnel is lack at present, the AHP can be used to determine the index weight when conducting the collapse risk analysis. At the same time, considering the subjectivity of the AHP method, the four weight calculation methods commonly used by AHP (geometric average, arithmetic average, feature vector method, and minimum square-multiply) can be combined to determine the weight values of each indicator as accurately and objectively as possible.

Table 1 Judgment matrix scale definition

| Scale | Meaning |
|---|---|
| 1 | Two factors are of the same importance |
| 3 | Two factors the former is slightly more important. |
| 5 | Two factors the former is obviously important |
| 7 | Two factors the former is very important |
| 9 | Two factors the former is extremely important |
| 2, 4, 6, 8 | Represents the median value of the adjacent scale |
| Countdown | The scale value after the two factors exchange the order of comparison |

#### 2.2.1 Basic principles of AHP

The application of AHP to determine the weight values of the evaluation system can be divided into four steps:

*(1) Build a hierarchical model*

When applying the AHP method to analyze the problem, it is necessary to hierarchical the indicator system, establish the hierarchical model, the number of models need to be determined according to the complexity of the problem but can be divided into three categories: the purpose layer, the standard layer, and the scheme layer. In the TBM collapse risk prediction model established in this paper, the risk level, the index type, and the specific indicators are corresponding.

*(2) Constructing a judgment matrix at all levels*

The proportions in the criteria layer and the scheme layer are different, and the indicators can be compared with each other in general, and the numbers 1 to 9 and their countdowns are used as the scale to determine the judgment matrix $A = \left(a_{ij}\right)_{n\times n}$. The definition of the determination matrix scale is shown in Table 1.

*(3) Hierarchical single sorting and consistency test*

After the judgment matrix is drawn from the scale of the indicators at all levels, the consistency test is needed to reduce the influence of subjective assignment of scale on the final result. The method is:

1) Calculating the *CI* (consistency index)

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

Where, is the maximum characteristic value of the determination matrix $\lambda_{\max}$.

2) Calculating the *CR* (consistency ratio)

$$CR = \frac{CI}{RI} \tag{2}$$

Table 2 Average random consistency metrics

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $RI$ | 0 | 0 | 0.52 | 0.89 | 1.12 | 1.24 | 1.36 | 1.41 | 1.46 |

Where $RI$ is the average random consistency indicator, as shown in Table 2.

When $CR$<0.1, it is considered acceptable to judge the consistency of the matrix, otherwise the judgment matrix should be corrected and re-tested until the consistency is met.

3) Total ordering and consistency test of the hierarchy

After obtaining the weights of each level and the indicators, it is necessary to further carry out consistency test on the total order of the hierarchy, and after passing the qualification, the final synthetic weight of each specific indicator at the scheme level can be calculated for the risk level of the target layer, and used it as an important basis for the calculation of risk prediction.

### 2.2.2 The weight calculation method based on AHP

In calculating the index weight, the AHP can use the geometric average, arithmetic average, feature vector method, and minimum square-multiply method, and there is a deviation in the index weight obtained by different calculation methods. In this paper, the weight of the four methods obtained index are combined to obtain the final weight vector of the indicator system, so as to reduce the result deviation caused by the subjectivity of the scale assignment. Assuming that matrix $A$ is an order of $n$, the four methods are calculated as follows:

*(1) Geometric average method*

The calculation process:

1) Multiplying each element of each row of matrix $A$ to get vector $A$';

2) Taking the nth root of each element of vector $A$' to get vector $A$''

3) Normalizing of each element of vector $A$' to get a weight vector.

The expression is

$$W_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}, \ i=1, 2, \ldots, n. \tag{3}$$

*(2) Arithmetic average method*

Considering that each column vector in the judgment matrix $A$ can approximate the distribution of the index weight, the arithmetic mean of all column vectors can be used to represent the weight vector of the indicator system.

The calculation process:

1) Normalizing each column vector of the judging matrix $A$ to get $A$', it is $a_{ij}^{'} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}$.

2) Adding each column vector and divided by $n$

The expression is:

$$W_i = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}, \ i=1, 2, \ldots, n. \tag{4}$$

*(3) Feature vector method*

By right-multiplying the weight vector $W$ by the judgment matrix $A$, we can get

$$AW = \lambda_{\max} W \tag{5}$$

Where, $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix $A$, exists and is unique, and the components of $W$ are all positive components. The final weight vector can be obtained by normalizing the obtained weight vector.

*(4) Least square method*

In determining the weights of each indicator, the weight vector can be determined by linear fitting method, so that the residual squares are minimum, even if the weight vector meets the following conditions

$$\begin{cases} \min Z = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(a_{ij}w_j - w_i\right)^2 \\ \text{s.t.} \ \sum_{i=1}^{n} w_i = 1 \end{cases} \tag{6}$$

Where, $w_i > 0$ , $i$=1, 2, …, $n$.

After deriving the index system weight matrix $W_1$, $W_2$, $W_3$, $W_4$ according to the above four methods, in order to reduce the subjectivity of the final weight, the four weight vectors must be averaged to obtain the final index weight vector $W$. That is

$$W = \frac{1}{4}\sum_{i=1}^{4} W_i \tag{7}$$

## 2.3 TBM tunnel collapse risk prediction method

### 2.3.1 The concept of normal cloud

After determining the indicator value and the weight vector, the collapse risk of the tunnel segment can be evaluated. In this paper, the normal cloud model algorithm is used to predict the collapse risk level of the TBM tunnel.

The normal cloud model is a model for transforming the uncertainty between qualitative concepts and quantitative values. It is widely used in many fields such as data mining, simulation prediction and evaluation (Wang *et al.* 2015, Hao *et al.* 2016). The basic principle is: suppose $Z$ is a quantitative domain expressed in precise values, $B$ is a qualitative concept on $Z$. If quantitative value $x \in Z$ and $x$ is a random implementation of qualitative concept $B$, the certainty degree of $x$ to $B$ is $\mu(x) \in [0, 1]$, which is a random number with a tendency to stabilize, and $x$ is normally distributed on domain $Z$, which is called a normal cloud, each $x$ value point is called a cloud drop. That is

$$\mu: Z \to [0, 1], \forall x \in Z_x \to \mu(x) \tag{8}$$

From the definition of the normal cloud model, it can be seen that this theory is a quantitative method to assign qualitative indicators, and the process of converting qualitative concepts into quantitative values is discrete and random. The values of each cloud droplet are modeled and are random values within a certain area, which can be described by its probability distribution function. In domain space, clouds made up of a large number of cloud droplets can be used to characterize qualitative concepts and use the expected $E_x$, entropy $E_n$ and hyper-entropy $H_e$ three numeric features are described quantitatively. Among them, $E_x$ is expected to represent the expectation of cloud droplets in the spatial distribution of the domain, that is, the central value of qualitative concepts in the domain space, and entropy $E_n$ indicates that qualitative concepts are uncertain


Fig. 2 The location of study area

in the domain space and the degree of dispersion of cloud drops, reflecting the range of values of cloud droplets used to describe qualitative concepts in the domain space, which is determined jointly by the randomness and fuzziness of qualitative concepts. Hyper-entropy $H_e$ describes the uncertainty of entropy $E_n$, reflecting the cohesion of the uncertainty of all cloud droplets used to describe the qualitative concept in the domain space, and its value indirectly reflects the thickness of the cloud droplets.

If $x$ is normally distributed in the domain $Z$, then $x$ satisfies $x \sim N\left(E_x, {E_n'}^2\right)$, where, $E_n' \sim N(E_n, H_e^2)$, and the certain degree of $x$ to $C$ is

$$\mu = \exp\left(\frac{-(x-E_x)^2}{2\left(E_n'\right)^2}\right) \tag{9}$$

### *2.3.2 Normal cloud prediction model for tunnel collapse*

If each collapse level corresponds to a "cloud" and the certainty degree of each tunnel segment to be predicted belonging to a collapse risk level obeys a normal distribution, the tunnel collapse risk prediction process based on AHP and normal cloud model is as follows:

1) Determining the collapse risk index system

When determining the tunnel collapse risk index, the TBM tunnel collapse risk index database can be established based on the domestic and international TBM tunnel related engineering examples and the collapse accident statistics. Based on the geological data of the tunnel segments to be evaluated, the appropriate risk indicators in the indicator database are selected to form a risk indicator system. It is worth noting that the risk indicator system should fully reflect the characteristics of the tunnel to be evaluated to ensure the accuracy of the prediction results.

2) Determine the values of each indicator and the value of the weight

According to the actual engineering, determine the range of values of each indicator in each risk level and assign values. Applying AHP, according to the Eqs. (3)-(7), the weight values of each indicator can be obtained, and the indicator weight vector $W$ can be established in a certain order.

3) Calculate the digital characteristics of each risk level cloud

Each risk level has three cloud digital characteristics, i.e., expect $E_x$, entropy $E_n$, and hyper-entropy $H_e$, the calculation formula is as follows

$$\begin{cases} E_x = \frac{C_{\max}+C_{\min}}{2} \\ E_n = \frac{C_{\max}-C_{\min}}{6} \\ H_e = k \end{cases} \tag{10}$$

Where, $C_{\max}$ and $C_{\min}$ are the maximum and minimum value ranges for a risk level corresponding to an indicator, respectively. are the maximum and minimum values of a certain risk level corresponding to a certain index. $k$ is a constant, which can be adjusted according to the value range of the variable to characterize the dispersion of entropy $E_n$. In this paper, $k$=0.01.

After the cloud digital characteristics are derived, the normal distribution of random numbers of cloud droplets can be generated, and the normal cloud generator generates a cloud model of each indicator for each collapse risk level.

4) Calculating comprehensive determination

According to the normal cloud generator algorithm, the certainty degree of each indicator belongs to a certain risk level can be obtained by the Eq. (9). Combined with the weight value of each indicator obtained by AHP, the comprehensive determination degree of the tunnel segment to be evaluated for a certain risk level can be calculated. The calculation formula is as follows

$$M = \sum_{i=1}^{n} \mu\omega_i \tag{11}$$

Comparing the comprehensive determination of the risk level of each section of the tunnel to be evaluated, the risk level corresponding to the maximum comprehensive determination is taken as the prediction result.

## 3. Engineering applications

### *3.1 Engineering conditions*

The location of the TBM2 construction section of the water supply project of the central city of Jilin Province is

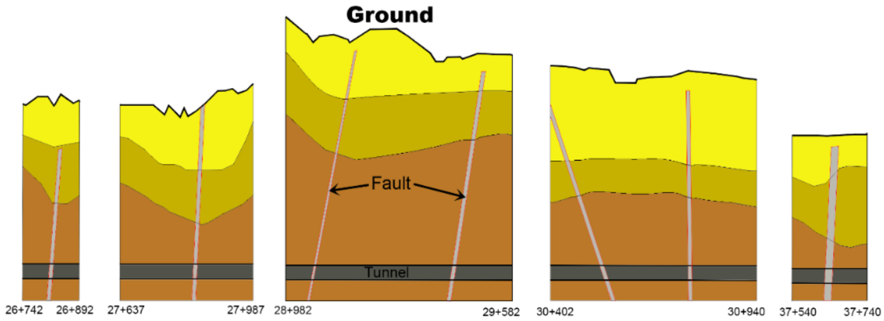


Fig. 3 Longitudinal section of the tunnel section to be evaluated

shown in Fig. 2, and the overall direction of the line is from north to east to west, with low hills and inter-phase ravines. Along with the terrain ups and downs, elevation range 254.8 to 493.7 m, the maximum depth of the cave 272.9 m. The main types of stratigraphic rock are a Jurassic group of Nanloushan rock, Anshan rock, two folding systems on the Fanjiatun group sandstone, ash rock, invasive rock for Yanshan period granite, quartz flash long rock. According to the composition, strength, structural characteristics and geological types of the rock and soil body (rock, age, etc.) the rocks in this segment are divided into two types, namely: medium hard rock-hard rock (sandstone, tuff), hard rock (granite, quartz flash long rock, Anshan rock).

The folds in this segment are not developed, and the fracture structure has the characteristics of inheritance and compound. A total of 24 faults and low-resistance abnormal zones intersecting with the body (including 15 faults, 7 detection anomalies, 2 remote sensing interpretation faults), 6 north-east, 4 north-west, 7 south-east and 7 south-west. The work area does not have a profound fracture in the project.

The surface water in the line area is controlled by the Songhua River water system, there are three main types of groundwater, namely, loose rock pore diving, debris rock pore fissure water and crystalline rock fissure water, aquifer thickness, abundant water volume, large water slope of groundwater and surface water, good runoff conditions.

According to the construction design plan, the tunnel can be divided into several sections according to the different surrounding rock levels, each section of the mileage continuous and the surrounding rock grade unchanged. In this paper, the five sections of 26+742~26+892, 27+637~27+987, 28+982~29+582, 30+402~30+940 and 37+540~37+740 (serial numbers are No. 1~No. 5) are selected as the prediction and evaluation objects, with relatively shallow buried depth, surrounding rock grade between IV~V, and relatively developed fault and low-resistivity anomaly zones. The collapse risk prediction model established in this paper is used to predict the risk grade, and the results are compared with the actual excavation results to verify the accuracy and reliability of the method. The geological profile of the fifth section to be evaluated is shown in Fig. 3.

### 3.2 Collapse risk prediction

As mentioned earlier, during the construction of the TBM tunnel, such factors as the depth of the tunnel and the diameter of the knife plate are important indicators to determine the degree of risk of collapse. In addition, when carrying out risk analysis on specific tunnels, the risk index system should be perfected in the light of its engineering conditions, so that the indicator system can fully reflect the characteristics of the project and ensure that all risk factors are considered and analyzed as necessary (Sapigni *et al.* 2002, Yagiz 2008).

Table 3 Grading standard for risk index of tunnel collapse

| Risk level | $R$ | $FPI$ | Effect width $D$/m | $K_v$ | $W/L\cdot(\text{min}\cdot\text{m})^{-1}$ |
|---|---|---|---|---|---|
| High Risk I | 0.0~2.5 | 0~50 | 20~50 | 0.0~0.2 | 120~150 |
| Higher risk II | 2.5~5.0 | 50~100 | 10~20 | 0.2~0.4 | 90~120 |
| Medium Risk III | 5.0~8.0 | 100~150 | 5~10 | 0.4~0.6 | 60~90 |
| Lower risk IV | 8.0~15.0 | 150~300 | 2~5 | 0.6~0.8 | 30~60 |
| Low Risk V | 15.0~25.0 | 300~600 | 0~2 | 0.8~1.0 | 0~30 |

According to the engineering geological data, the five tunnel sections selected in this paper have fault and fissure development, with the hole line intersection angle is larger, the width is more than 5 to 7 mm, filling to quartz, jade myelin and calcite-based, crisscrossed, local mesh the surrounding rock conditions are poor, mostly IV-V class surrounding rock. Some tunnel sections of the surface features are hilly river valleys, perennial flowing water. The rock is complex and frequent changes, many are block structure, groundwater development.

In the light of the above-mentioned TBM tunnel characteristics and the actual conditions of the project, the index system used to predict the risk level of the tunnel collapse should include six items: tunnel depth $H$, knife plate diameter $D$ (or tunnel span), field penetration index $FPI$, degree of development of fault and broken zones, surrounding rock levels, and groundwater conditions. To simplify the indicator system, the buried depth and span metrics can be combined into the over-span ratio $R=H/D$.

Of the above five indicators, the over-span ratio $R$ and the field penetration index $FPI$ are quantitative indicators and can be directly valued; The surrounding rock grade and groundwater condition are qualitative indicators, which need to be converted into quantitative representation for calculation. In this paper, these three qualitative indicators are $d(m)$ of the effect width of the fault and broken band in the surrounding rock, respectively, and the rock body integrity index $Kv$ and every meter of the hole. Every

Table 4 Indicator values for tunnel segments to be evaluated

| Tunnel segment number | $R$ | $FPI$ | Effect width $D$/m | $K_v$ | $W/L\cdot$ (min·m)$^{-1}$ |
|---|---|---|---|---|---|
| 1 | 10.7 | 144 | 3.4 | 0.43 | 61 |
| 2 | 9.9 | 127 | 6.8 | 0.43 | 55 |
| 3 | 13.8 | 236 | 2.2 | 0.26 | 128 |
| 4 | 12.4 | 312 | 1.3 | 0.29 | 106 |
| 5 | 9.0 | 275 | 1.0 | 0.28 | 33 |

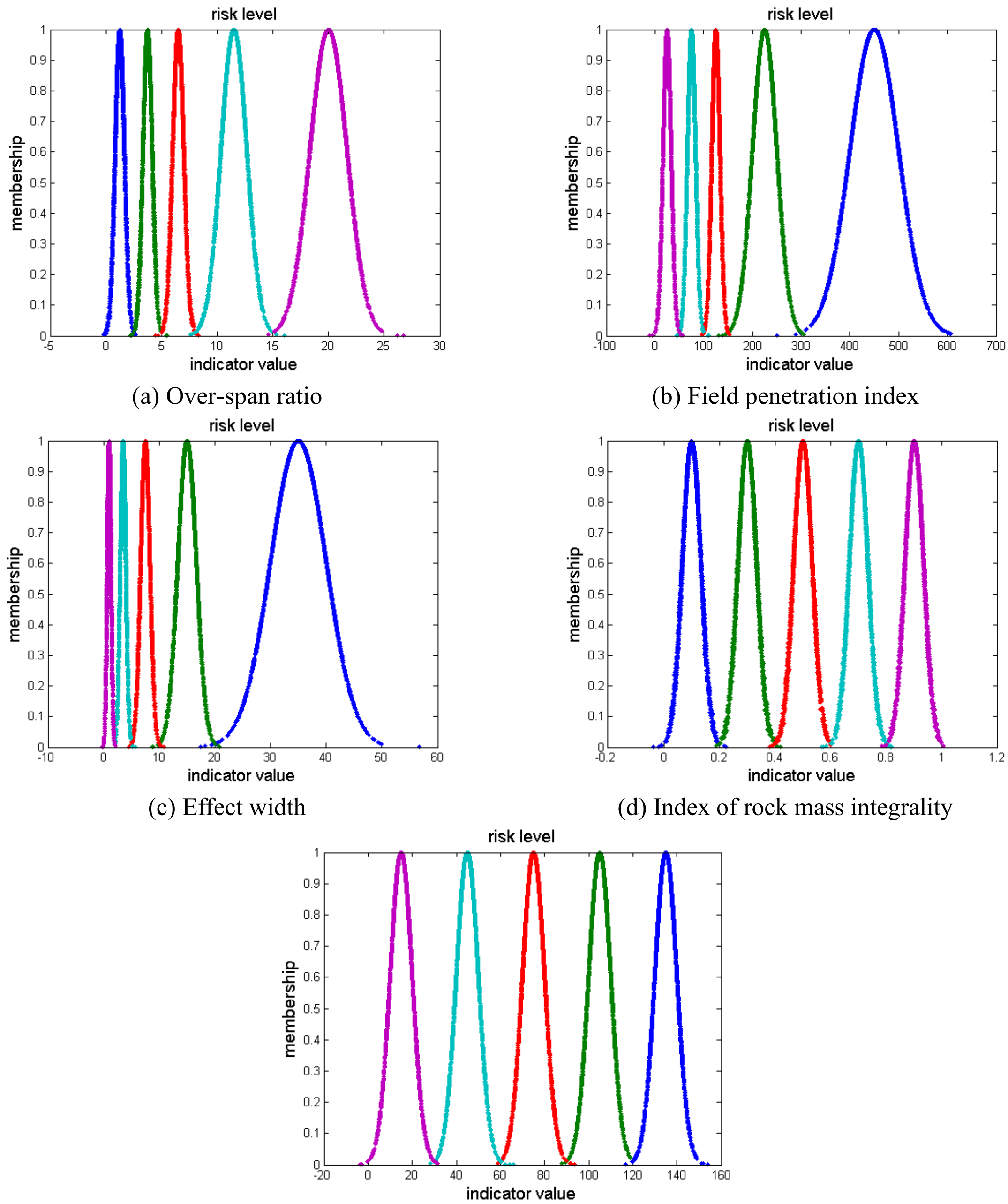
Table 5 Weight values for each indicator

| Method | $R$ | $FPI$ | Effect width $D$/m | $K_v$ | $W/L\cdot$ (min·m)$^{-1}$ |
|---|---|---|---|---|---|
| Geometric average | 0.1217 | 0.0832 | 0.2711 | 0.3326 | 0.1914 |
| Arithmetic average | 0.1458 | 0.0772 | 0.2591 | 0.3271 | 0.1908 |
| Feature vector | 0.1292 | 0.1003 | 0.2613 | 0.3277 | 0.1815 |
| Least square | 0.1301 | 0.0914 | 0.2588 | 0.3279 | 0.1918 |
| Average weight | 0.1317 | 0.0880 | 0.2626 | 0.3288 | 0.1889 |

minute water seepage $W/L$ (min.m)$^{-1}$ (Qiu *et al.* 2014, Jiao *et al.* 2015, Li *et al.* 2015). In the condition of IV~V surrounding rocks, the landslide risk classification standards corresponding to each index are shown in Table 3.

The value of the five-hole segment indicators as shown in Table 4.

The digital features of the normal cloud model can be obtained from Eq. (10), where $k$ is 0.01. The evaluation




(a) Over-span ratio (b) Field penetration index

(c) Effect width (d) Index of rock mass integrality

(e) Water seepage per minute

Fig. 4 Normal cloud model of risk levels for each indicator

Table 6 Comprehensive certainty degree of the collapse risk in each tunnel segment

| Tunnel segment | Comprehensive certainty degree at each level | | | | | Prediction level | Actual level |
|---|---|---|---|---|---|---|---|
| | I | II | III | IV | V | | |
| 1 | 0.0012 | 0.1517 | 0.3319 | 0.3517 | 0.3014 | IV | IV |
| 2 | 0.0658 | 0.2611 | 0.4019 | 0.2982 | 0.1534 | III | III |
| 3 | 0.2667 | 0.5137 | 0.3625 | 0.1782 | 0.2583 | II | II |
| 4 | 0.1704 | 0.3325 | 0.3108 | 0.2101 | 0.0015 | II | III |
| 5 | 0.0079 | 0.2583 | 0.2967 | 0.2080 | 0.0526 | III | III |

model of each indicator is shown in Figs. 4(a)-(e).

By Eqs. (3)-(7), the AHP can be applied to calculate the weight value of each indicator. In the process of calculation, the judgment matrix $A$ is as follows, and the weight value and final weight value obtained by the four basic methods are shown in Table 5.

$$A = \begin{pmatrix} 1 & \frac{1}{3} & 4 & 6 & 2 \\ 3 & 1 & 7 & 8 & 4 \\ \frac{1}{4} & \frac{1}{7} & 1 & 2 & \frac{1}{2} \\ \frac{1}{6} & \frac{1}{8} & \frac{1}{2} & 1 & \frac{1}{3} \\ \frac{1}{2} & \frac{1}{4} & 2 & 3 & 1 \end{pmatrix}$$

The value of each indicator of each hole segment is entered into the Eq. (9), the indicators can be obtained for each collapse risk level of determination, and then the calculation results into the Eq. (11), can be assessed tunnel segment for the comprehensive determination of each risk level, and then determine the final collapse risk prediction level. After the excavation of the tunnel section studied in this paper, the risk level is divided according to the deformation quantity, deformation speed and stress acting on the support of the surrounding rock in a certain time, combined with relevant engineering experience. The prediction results are compared with the actual excavation results, as shown in Table 6.

By comparing the prediction results of each tunnel section using the prediction model in this paper and the collapse risk level determined according to the actual excavation results, it can be seen that this prediction method is accurate and practical. In these five tunnel sections, the prediction results of sections 1, 2, 3 and 5 are consistent with the field analysis results after actual excavation. Although there are differences in the result of section 4, according to the calculation results of the comprehensive certainty degree in Table 6, there is little difference in the level II and level III in the result of section 4, indicating that the result of section 4 is also meaningful.

## 4. Discussion

1. In selecting the risk index, the method of determining the index system for risk prediction is determined by further analyzing the engineering conditions of the tunnel to be evaluated on the basis of statistical analysis of similar tunnel projects. The advantage of this method is that the index system obtained can not only fully consider the common characteristics of the same type of project, but also fully reflect the characteristics of the project. However, because the current TBM tunnel engineering data compared to the traditional excavation method (such as drilling and blasting method) of the tunnel is still relatively lacking, and the same TBM tunnel is also divided into the submarine tunnel, mountain tunnel, and other types. As a result, it is still difficult to ensure comprehensiveness in the initial identification of the indicator system. With the increasing number of TBM tunnels and the continuous improvement of relevant information, a database of geological hazard risk indicators of TBM tunnels can be established as the basis for the selection of risk indicators in related research such as risk prediction. So that the index system is more scientific and comprehensive, improves the accuracy of the prediction results.

2. Due to the small number of TBM tunnel collapse cases, common objective weight algorithms (such as rough set theory, weight inverse analysis method, etc.) are difficult to apply to the calculation of the weight value of each risk index in this model. Therefore, this paper adopts the AHP. Because this method needs to be subjectively sorted by the importance of the indicators, the resulting weight value inevitably has a certain degree of subjectivity. By comparing the commonly used four-level analysis weight algorithm, and taking the mean of the results obtained by the four methods as the final weight of the indicator system, this paper tries to minimize the negative impact of subjectivity. If a complete database of bad geological hazards in the TBM tunnel can be established, the weight of the risk index can be calculated using a more considerable method, so that the prediction results can be more accurate.

3. In the process of tunnel construction, subjective factors such as the strength and closing time of support, the engineering experience and management level of construction units are also important indicators that affect the amount of deformation and collapse risk of the tunnel. However, in view of the current TBM construction norms have been relatively sound, construction management is more stringent, so the forecast model established in this paper no longer consider such indicators, only buried depth, groundwater conditions and other objective factors to analyze, and on this basis to predict the risk level of tunnel collapse.

## 5. Conclusions

1. In this paper, a risk index system is established with tunnel over-span ratio, field penetration index, fault and fracture band effect width, rock body integrity index and per minute seepage of water per meter of hole, and a model for prediction of collapse risk level is carried out using analytic hierarchy process and normal cloud model theory. By comparing and verifying the excavation results, it can be seen that the TBM tunnel collapse risk prediction model established in this paper is basically in line with the actual engineering, and the

prediction results can provide effective guidance for construction.

2. Observing the calculation results of the prediction model, it can be known that the comprehensive determination degree of multiple risk levels corresponding to the same tunnel segment may be small. This means that the predicted result should be an interval rather than a specific value. Moreover, during the actual excavation process, the risk level of the collapse may be changed due to construction disturbances and other factors. Therefore, when comparing the comprehensive determination degree of each risk level, in addition to the risk level with the largest comprehensive degree of determination, the risk level with a greater comprehensive degree should also be considered.

3. In the previous tunnel risk prediction model, the same index system is often used for similar tunnels, which inevitably leads to the neglect of some engineering features of the object to be evaluated, which affects the final accuracy. Based on the reference to similar engineering examples, this paper fully considers the actual working conditions of the tunnel section to be evaluated and establishes an index system that can fully consider the characteristics of the tunnel, so as to improve the accuracy of the prediction results. This also shows that considering the characteristics of the object to be evaluated is an important way to improve the accuracy of the prediction results.

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