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Research article

Dynamic risk evaluation method for collapse disasters of drill-and-blast tunnels: a case study

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Abstract: The tunnel collapse is one of the most frequent and harmful geological hazards during the construction of highway rock tunnels. As for reducing the occurrence probability of tunnel collapse, a new dynamic risk assessment methodology for the tunnel collapse was established, which combines the Cloud model (CM), the Membership function, and the Bayesian network (BN). During the preparation phase, tunnel collapse risk factors are identified and an index system is constructed. Then, the proposed novel assessment method is used to evaluate the probability of tunnel collapse risk for on-site construction. The probability of tunnel collapse risk in the dynamic process of construction can provide real-time guidance for tunnel construction. Moreover, a typical case study of the Yutangxi tunnel is performed, which belongs to the Pu-Yan Highway Project (Fujian, China). The results show that the dynamic evaluation model is well validated and applied. The risk value of tunnel collapse in a construction cycle is predicted successfully, and on-site construction is guided to reduce the occurrence of tunnel collapse. Besides, it also proves the feasibility of the dynamic evaluation method and its application potential.

Keywords: cloud model; Bayesian network; dynamic risk assessment; exposure degree; membership function

1. Introduction

At present, the drilling and blasting method is still the most economical and efficient construction method. However, it involves many risk factors and complex construction procedures, resulting in a relatively high rate of collapse accidents [1]. The mountain tunnel collapse mainly occurs in areas with poor stability of surrounding rocks affected by the weathering zones, the fault fracture zones, the bad geological bodies, and the geological structural zones [1]. Once the tunnel collapse occurs, it may cause serious economic losses, construction delays, and even human casualties. Therefore, it is necessary to study the risk mechanism of the tunnel collapse by considering the accident scenario and the real-time safety analysis, aiming to provide decision support for assuring the safety of tunnel construction.

In the past few decades, many researchers have focused on performing risk assessments of tunnel collapse. Wu et al. [2] used Bayesian networks to provide support for tunnel construction safety analysis and thus increased the likelihood of a successful project in a dynamic project environment. Liu et al. [3] proposed a reliability analysis method using the copula model to provide guidelines for tunnel face stability control under uncertainty and randomness. Other methods, such as the conventional Fault Tree and the Event Tree, were also used to perform a risk assessment of the tunnel collapse [1,4,5].

However, the above-mentioned methods are static, and the states of the variables implemented in these methods are binary (“Yes” and “No”) to model an accident scenario [6]. Considering the limitations of these types of conventional methods, synthetic methods, such as the Artificial Neural Network, the Fuzzy System, the Support Vector Machines, and the Comprehensive Evaluation Method, have been employed [7–11]. These comprehensive methods can set multiple levels of accident consequences and make semi-quantitative decisions. In the risk analysis process, each variable has more than two states, and each state has a corresponding graded score given by experts. In the grading system, a smaller subdivision of grades indicates a more accurate result. However, the smaller subdivision of risk factor status, the more difficult it is to give a final opinion. When associated parameters, such as the geological, the construction, and the design parameters changed, the aforementioned methods cannot accurately describe the updated features of dynamic environments as the construction progress evolves.

Recently, the Bayesian network (BN) has been proposed to model the complexity in man-machine systems. The BN theory can describe dependencies between variables both qualitatively and quantitatively, and it is suitable for knowledge representation and reasoning [12]. Also, the BN theory is powerful in processing uncertain information and it can be used for reliability and failure analysis in complex environments [13]. For a dynamic risk assessment of complex systems, the BN method is flexible in updating the probability with the newly provided evidence.

However, the BN does not consider the impact of the risk factor’s exposure degree on the risk value. When the hazard-bearing body is exposed to the impact of the hazard factor, it will show vulnerability and generate risk. Yu et al. [14] used an exposure degree to express the hazard level of risk factors. The exposure degree is a function of time, so membership functions in fuzzy mathematics are proposed to express the degree of exposure to risk events. The exposure degree of risk factors changes over time, making the final risk value more in line with the actual situation. The Bayesian network is appropriate for representing a large variety of uncertain scenarios because multi-state BN nodes can be established. However, as the node status increases, the scale of the conditional probability table increases exponentially. (For example, assuming that each node has 4 states, a child node with 4 parent nodes has a conditional probability table containing 256 combinations.) At present, the generation of the conditional probability table (CPT) still relies on experts for scoring, which will greatly increase the workload of experts.

In response to the above problems, a dynamic risk assessment based upon the Cloud model, the exposure degree, and the BN is developed. This model aims to achieve the following goals: (1) The Bayesian Networks (BN) is used to investigate causal relationships between the tunnel collapse and its influential variables based upon the risk/hazard mechanism analysis; (2) The Cloud model generates CPT through the weight of the root node, reducing the workload of experts. (3) The updating of the Bayesian network root node state can guide the whole life cycle safety management of tunnel construction, including pre-construction, during-construction, and post-accident control. Finally, the novel approach has been successfully applied in the case of the Yutangxi tunnel of the Pu-Yan Highway (Fujian, China). The results demonstrate the feasibility of the proposed new dynamic evaluation method and its application potential.

2. Methodology

2.1. Exposure degree

The concept of membership in fuzzy mathematics is proposed to calculate the exposure of the risk factors. So that time variables can be used to quantitatively calculate the degree of exposure, to achieve the effect of the dynamic risk assessment.

A fuzzy set can be presented as:

$$B(x)=\{(x,\mu_A(x)),x\in X\},\mu_A(x):X\rightarrow[0,1] \tag{1}$$

where X is a universal set of variable x, $B(x)$ is a fuzzy set of X, and $\mu_A(x)$ is the degree of membership for x in B.

The value $\mu_A(x)$ ranges from 0 to 1. A higher $\mu_A(x)$ indicates a stronger association between x and B. The fuzzy sets are presented by membership functions, such as the triangular and the trapezoidal membership functions. The trapezoidal and the triangular membership functions are most commonly used in engineering. The $\mu_A(x)$ of x (x $\in$ [a, b]) to the triangular and the trapezoidal membership functions can be calculated using Eqs (2) and (3), respectively.

$$\mu_A(x)=\begin{cases} 0, x\le a \\ \frac{x-a}{m-a}, a<x\le m \\ \frac{b-x}{b-m}, m<x<b \\ 0, x\ge b \end{cases} \tag{2}$$

$$\mu_A(x)=\begin{cases}0, x\le a\\ \frac{x-a}{b-a}, a<x\le b\\ 1, b<x\le c\\ \frac{d-x}{d-c}, c<x\le d\\ 0, x>d\end{cases} \tag{3}$$

The exposure degree is a function of time. According to the actual needs of the project, this article adopts the trapezoidal membership function Eq (3), as shown in Figure 1.

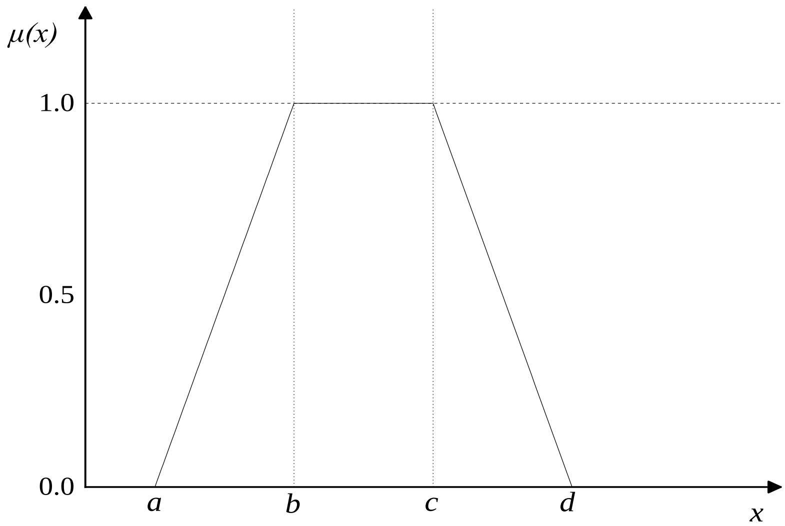

Figure 1. trapezoidal membership function.

2.2. Normal cloud model

Because there are many introductions to the theory of CM algorithms [7,15], this article ignores such discussions. Let X be the universe of discourse and B be a qualitative concept connected with X. If there is a number x, (1) $x\in X$, (2) x is a random instantiation of concept B, (3) x satisfies Eq (4), the grade of a certain degree of x belonging to concept B satisfies Eq (5) [15]:

$$\begin{cases} x\sim N\left(Ex, En'^2\right)\\ En'\sim N\left(En, He^2\right)\end{cases} \tag{4}$$

$$\mu(x)=e^{-\frac{(x-Ex)^2}{2(En')^2}} \tag{5}$$

Various tunnel collapse risk factors B_i are analyzed in the decision-making process. To explore useful information, each risk factor should be further divided into different risk states B_{ij} (I = 1, 2, …, M; j = 1,2, …, N). Each risk state can correspond to a specific double limit interval, denoted as [$b_{ij}(L)$, $b_{ij}(R)$]. The conversion from the double limit interval [$b_{ij}(L)$, $b_{ij}(R)$] to the normal cloud model

$\left(Ex_{ij}, En_{ij}, He_{ij}\right)$ can be achieved by Eq (6).

$$\begin{cases} Ex_{ij} = \dfrac{b_{ij}(L) + b_{ij}(R)}{2} \\ En_{ij} = \dfrac{b_{ij}(R) - b_{ij}(L)}{6}, \quad \left(i = 1, 2, \ \ldots, M; j = 1, 2, \ \ldots, N\right) \\ \quad He_{ij} = h \end{cases} \tag{6}$$

where, "Ex_{ij}" is the expectation; "En_{ij}" is the entropy of "Ex_{ij}", "He_{ij}" is the Hyper-entropy. The range of the constant "h" is from 0 to "En_{ij}" which is adapted to reflects the uncertainty degree of those factors. "h" is set to 0.01 in this paper.

2.3. Bayesian network

The Bayesian network (BN) is a combination of two different mathematical areas, graph theory, and probability theory [2]. It consists of a directed acyclic graph (DAG) and an associated joint probability distribution (JPD) [16]. A BN model with n nodes can be represented as $B\langle G, \Theta\rangle$, where G stands for a DAG with n nodes and Θ is defined as the JPD of the BN model. A general BN intuitively represents a complex network with n nodes and direct edges. The nodes $\{X_1, \cdots, X_n\}$ in the graph are labeled by related random variables. The directed edges between the nodes represent association relationships among the variables. Each node is attached to a conditional probability table (CPT) that contains the conditional probability of the parent node.

Assuming $parents(X_i)$ is the parent nodes of X_i in the DAG, the conditional probability distribution of X_i is defined as $P\left(X_i \middle| parents(X_i)\right)$. The calculation of $P(x)$ can be written as Eq (7).

$$P(x) = P(X_1, \cdots, X_n) = \prod_{X_i \in \{X_1, \cdots, X_n\}} P\left(X_i \middle| parents(X_i)\right) \tag{7}$$

2.4. Conditional probability table (CPT) construction

In order to reduce the workload of experts, the Cloud model is adopted to build CPT through root node weights. Figure 2 proposes an overview of the flowchart of the CPT construction, which can be divided into three parts: (1) Weight calculation: Calculate the combination weight of risk factors in different states; (2) Cloud model conversion: Establish the normal cloud generator for the different combinations; (3) Conditional probability conversion: Different combination weights are transformed into distribution probability by the normal cloud generator.

(1) Weight calculation

The weight calculation is divided into four parts: (1) parent node weight; (2) state weight; (3) state influence factor; (4) state combination weight. The result of the weight calculation is the state combination weight, which is the basis for building the cloud family and generating the conditional probability table.

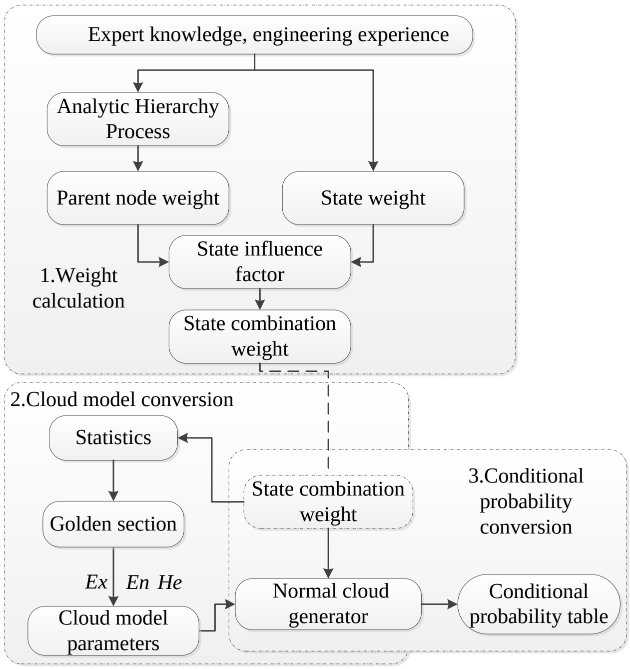

Figure 2. Generation process of conditional probability table based on FNCT**.**

The parent node weight (*WA*) indicates the influence of a single parent node on the child node. In this study, the *WA* was calculated by a pairwise contrast matrix [17], which quantitatively evaluates the influence of related factors on tunnel collapse. The weighted values can be evaluated through a simple pairwise comparison [18].

The state weight (*WS*) represents the influence of the state changes of the parent node on the child node, and each state division corresponds to a set of the state weight. The state weight (*WS*) is divided into four levels represented by "I-IV" as seen in Table 1.

Table 1. Setting of state weight level.

Level	I	II	III	IV
Score	1	3	5	7

The state influence factor (*WAS*) is the product of the parent node's weight and its state weight, representing the influence of each state of a single parent node on the child node. Assuming the weight of the *i*-th parent node is WA_i. The parent node has *S* states, represented by WS_i^s. Then the influence factor of each state of the parent nodes can be seen in Eq (8).

$$WAS_i = \left\{ WA_i \times WS_1^s, WA_i \times WS_2^s, \cdots, WA_i \times WS_s^s \right\} \tag{8}$$

The state combination weight (*WCS*) is the sum of the *WAS* of each node state under the state combination, representing the influence of the state combination of all parent nodes on the child nodes. The state combination weight of the state combination can be seen in Eq (9).

$$WCS_q = \sum_{i=1}^{n} WAS_i \tag{9}$$

where n stands for the number of the parent nodes, q stands for the combination of different states of each parent node.

(2) Cloud model conversion

The cloud model conversion refers to the conversion of the combined weights into conditional probabilities by the normal cloud generator. Each normal cloud generator corresponds to the state of the parent node and contains three parameters (*Ex*, *En*, *He*). The values of these three parameters are calculated by Eq (6).

(3) Conditional probability converter

The certainty degree of each combination is obtained through the normal cloud generator. The obtained certainty degree of each cloud is consistent with the probability of the variable[19]. The certainty degrees can be converted to probabilities by Eq (10).

$$P(u_i) = \frac{\mu(u_i)^{1/\alpha}}{\sum_{i=1}^{k} \mu(u_i)^{1/\alpha}} \tag{10}$$

where α ($0 < \alpha \le 1$) is constant. The certainty degree is more consistent with the probability when α is close to one. This paper α takes 1.

(4) Cloud model accuracy validation

Assuming that the risk index is quantified using a hundred marks system, the risk index is divided into four levels. That is to say, the risk grades of I, II, III, and IV are assigned a range of [75, 100], [50, 75], [25, 50], and [0, 25], respectively. The hyperparameters of the Cloud model are calculated by Eq (6), as shown in Table 2. In the meantime, during the transformation process from an interval to a cloud model, special treatments should be given to the starting and ending cloud models of a specific factor. In this research, when the value of the risk indicator is lower than 12.5 (or higher than 87.5), the membership degree of risk indicator within the cloud model IV (or I) is defined to be one.

Figure 3 illustrates the distribution of Cloud models for the risk indicator. When the risk indicator takes the value of 26, the probability value of each risk level of the risk indicator is obtained through the cloud generator, as shown in Table 2. The probability of the risk value being in level III is 0.81 and in level IV is 0.19. The results are in line with the actual situation and verify the feasibility of the Cloud model to generate conditional probabilities.

Table 2. The value of the Cloud model hyperparameters.

Risk level	I	II	III	IV
Ex	87.5	62.5	37.5	12.5
En	4.167	4.167	4.167	4.167
He	0.01	0.01	0.01	0.01
Probability	0	0	0.81	0.19

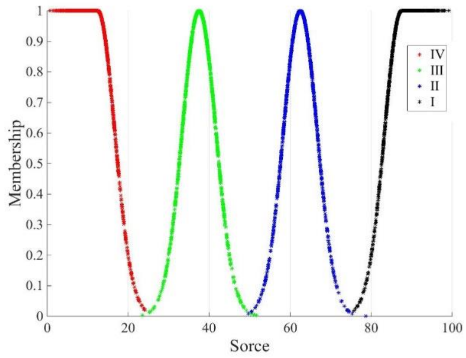

Figure 3. Distribution of cloud models for the risk indicator**.**

3. Tunnel collapse risk assessment

(1) Collapse risk calculation

Both domestic and foreign standards [20–22] define the risk value as the product of the risk probability and the loss caused by the risk, as shown in Eq (11).

$$R = P \bullet C \tag{11}$$

where P is the risk probability, C is risk loss.

However, Eq (11) is generally applied to static risk assessment and cannot be directly applied to dynamic risk assessment. Therefore, this paper proposes a novel risk calculation formula combined with the exposure degree and the weight of risk factors, as shown in Eq (12). The framework of tunnel collapse risk assessment is shown in Figure 4.

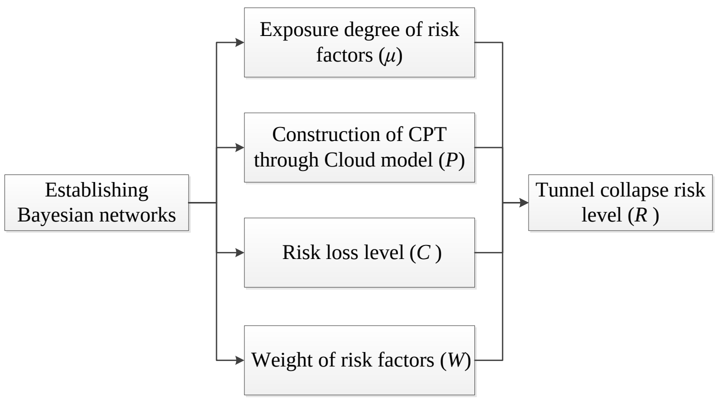

Figure 4. Framework of the proposed method.

The method realizes real-time risk assessment of the construction process through the following three points. First, the risk factor status is updated in real-time, enabling dynamic assessment of tunnel collapse risk. Second, the exposure degree of risk factors is used to define the degree of influence of risk factors over time. Third, the reasoning advantage of the Bayesian network is used to conduct a reverse analysis of the accident to obtain the main reason for the accident and propose corresponding recommendations.

$$R = \sum P \bullet C \bullet \mu \bullet G \tag{12}$$

where P is the probability of risk, C is the risk loss level, μ is the exposure degree, G is the weight of risk factors.

(2) Collapse accident diagnosis

When a collapse accident occurs, the main cause of the collapse can be diagnosed based on the product of the weight and the exposure degree, as shown in Eq (13). When W is larger, it means that the risk factor has a greater impact on the collapse risk of the construction section. Therefore, when a collapse event occurs, the construction unit can prioritize the inspection of risk factors with high value of W. In this way, emergency rescues can be carried out as soon as possible, thereby reducing the loss of economic and personnel.

$$W = \mu \bullet G \tag{13}$$

where μ is the exposure degree, G is the weight of risk factors.

4. Case study

The Yutangxi tunnel is a twin-tube highway tunnel located in Sanming, Fujian Province. This paper takes the right line (K244+885~K245+840) as the object of the study. The longitudinal section of the Yutangxi tunnel is shown in Figure 5. There are 465m of V-level surrounding rock section and 435 m of IV-level surrounding rock section. The rock mass is mainly composed of residual silty clay, granite fully weathered layer, and broken strong weathered layer. Furthermore, the tunnel contains two fault zones L1 and L2. During the construction process, it is easy to cause tunnel collapse. Therefore, it is urgent to conduct a collapse risk assessment of this tunnel section to reduce the losses caused by the collapse. In the proposed novel risk assessment method, the following four steps are adopted:

Step (1) Risk/Hazard factors identification: The risk mechanism of tunnel collapse is analyzed to reveal the potential on-site risk factors.

Step (2) Establishment of a BN model: The potential risk/hazard factors and their causal relationships are revealed, and then the root nodes (RNs), the intermediate nodes (INs), and their leaf nodes (LNs) are identified.

Step (3) Establishment of the conditional probability tables (CPT): The weights of the risk factors are converted into distribution probabilities through the normal cloud generator, and eventually the conditional probability table is obtained.

Step (4) Calculation of the collapse risk value: A novel assessment method combining the exposure degree were proposed, and the risk weights were applied to calculate the overall risk value of collapse.

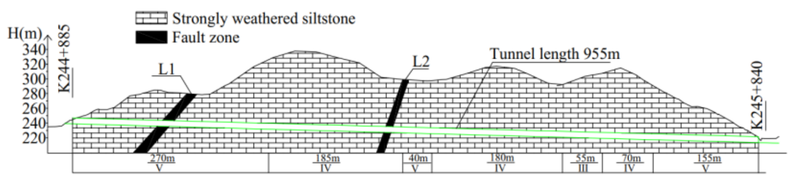

Figure 5. The longitudinal section map of the Yutangxi tunnel project.

4.1. Risk/hazard factors identification

For the drilling and blasting tunnel construction, many scholars have carried out extensive researches on the risk factors of collapse [1,23–26]. Referring to previous researches, the risk list is selected, as shown in Table 3. The risk factors are analyzed in detail in those research [1,27]. The risk factors are divided into four types: construction risk, natural risk, geological risk, and environmental risk. It is equivalent to using the checklist method to identify the risks and screen out the risks existing in the construction.

Table 3. Risk factors of tunnel collapse.

Risk unit	Risk event (risk factor)
Drilling and blasting operations(B_1)	Drilling(X_1)
	Overbreak or underbreak(X_2)
	Dangerous stone removal(X_3)
Initial support(B_2)	Advance support(X_4)
	Vertical arch spacing(m) (X_5)
	Laying steel mesh(X_6)
	Shotcrete thickness(cm) (X_7)
Secondary lining(B_3)	Laying a waterproof layer(X_8)
	Tying secondary lining steel bars(X_9)
	Pouring secondary lining concrete(cm) (X_{10})
Bad hydrogeology(B_4)	Rainfall(mm)(X_{11})
	Groundwater level(X_{12})
	Surface water leakage(X_{13})
Bad engineering geology(B_5)	Integrity degree (X_{14})
	Weak structural plane(X_{15})
	Special soil(X_{16})
Field exploration(B_6)	Geological Prospecting(X_{17})
	Advanced geological forecast(X_{18})
	Monitoring measurement(X_{19})
	Surrounding rock grade (km/s)(X_{20})
Construction design plan(B_7)	Excavation method(X_{21})
	Excavation span (m)(X_{22})
	Tunnel depth (H/m) (X_{23})
	Blasting parameter selection(X_{24})

4.2. Establishment of a BN model and create evaluation criteria

(1) Establishment of a BN model

The occurrence of tunnel collapse is a complicated process with numerous influencing factors and a high degree of randomness. Furthermore, the relationship between the various factors is highly nonlinear. According to section 4.1, a tunnel collapse Bayesian network (TCBN) is established (see Figure 6); where 24 root nodes contribute to the failure of the leaf node (tunnel collapse). The descriptions of all nodes are illustrated in Table 3.

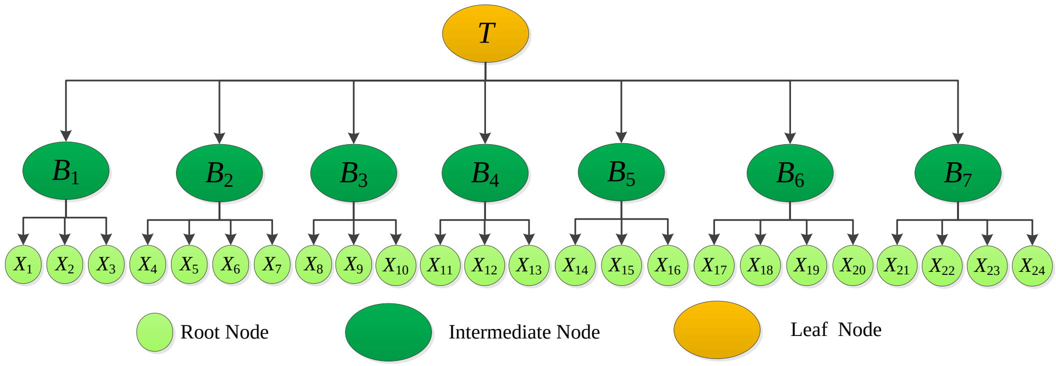

Figure 6. Layered structure of risk factors for tunnel collapse.

(2) Establishment of the evaluation criteria

Due to the complex tunnel construction environment, the status of risk factors is often difficult to determine with the conventional two statuses. Therefore, this article divides the risk factors into four grades [1,23,26], as shown in Table 4.

Table 4. Classified states of tunnel collapse Bayesian network nodes.

Layer	Grade division			
	I	II	III	IV
Tunnel collapse (T)	No risk (0~25)	Low risk (25~50)	Medium risk (50~75)	High risk (75~100)
Drilling and blasting operations(B_1)	No risk	Low risk	Medium risk	High risk
Initial support(B_2)	No risk	Low risk	Medium risk	High risk
Secondary lining(B_3)	No risk	Low risk	Medium risk	High risk
Bad hydrogeology(B_4)	No risk	Low risk	Medium risk	High risk
Bad engineering geology(B_5)	No risk	Low risk	Medium risk	High risk
Field exploration(B_6)	No risk	Low risk	Medium risk	High risk
Construction design plan(B_7)	No risk	Low risk	Medium risk	High risk
Drilling(X_1)	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Overbreak or underbreak(X_2)	Normal	Underbreak	Overbreak	Severe overbreak
Dangerous stone removal(X_3)	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Advance support(X_4)	Long tube shed	Advanced double-layer small catheter	Leading single-layer small catheter	Leading anchor
Vertical arch spacing(m) (X_5)	0.35~0.55	0.56~0.75	0.76~0.85	0.86~1.0
Shotcrete thickness(cm) (X7)	27~29	25~27	23~25	20~23
Laying a waterproof layer(X8)	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Tying secondary lining steel bars(X9)	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Laying steel mesh(X_6)	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable

Continued on next page

Layer	Grade division			
	I	II	III	IV
Pouring secondary lining concrete(cm) (X_{10})	55~60	50~55	45~50	40~45
Rainfall(mm)(X_{11})	0~25	25~50	50~100	100~200
Groundwater level(X_{12})	60m≤h<100m	30m≤h<60m	0m≤h<30m	h<0m
Surface water leakage(X_{13})	Undeveloped and the surrounding rock is dry	Less developed, and the surrounding rock is damp	Weakly developed, and there is a small amount of fissure water	Developed
Integrity degree (X_{14})	$1 \geq k_v > 0.75$	$0.75 \geq k_v > 0.55$	$0.55 \geq k_v > 0.25$	$0.25 \geq k_v > 0$
Weak structural plane(X_{15})	Very rough and discontinuous	Rough and slightly open	Slippery surface and slightly open	Slippery surface and open
Special soil(X_{16})	No risk	Low risk	Medium risk	High risk
Geological Prospecting(X_{17})	Accurate	Almost accurate	Inaccurate	Extremely inaccurate
Advanced geological forecast(X_{18})	Accurate	Almost accurate	Inaccurate	Extremely inaccurate
Monitoring measurement(X_{19})	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Surrounding rock grade (km/s)(X_{20})	$5.5 \geqslant V_P > 4.5$	$4.5 \geqslant V_P > 3.5$	$3.5 \geqslant V_P > 2.5$	$2.5 \geqslant V_P > 0$
Excavation method(X_{21})	Reasonable	Almost reasonable	Unreasonable	Extremely unreasonable
Excavation span (m)(X_{22})	0~7	7~10	10~14	15~30
Tunnel depth (H/m) (X_{23})	60~150	40~60	15~40	0~15
Blasting parameter selection(X_{24})	$b >> R$	$b > R$	$b = R$	$b < R$

where V_P means the longitudinal wave velocity; R is the safety allowable distance of blasting vibration; b is the Distance between two-lane tunnels.

In order to simplify the analysis, each qualitative index is quantified using a hundred marks system in this study, the qualitative index is divided into four levels. That is to say, the risk grades of I, II, III, and IVare assigned a range of [75, 100], [50, 75], [25, 50], and [0, 25], respectively.

For the integrity degree (X_4), the coefficient of the rock mass integrity can be used to reflect the grade about integrality of the rock mass, and can be expressed by Eq (14) [28]:

$$k_v = \frac{v_{pm}^2}{v_{pr}^2} \tag{14}$$

where v_{pm} is the rock mass elastic longitudinal wave velocity, and v_{pr} is the rock elastic longitudinal wave velocity. The value of v_{pm} can be estimated from tunnel seismic prediction (TSP).

For the explosive design (X_7), R is obtained according to Chinese standard "Safety regulations for blasting" (GB6722-2014), which is shown in Eq (15). By comparing b and R, we can judge whether the explosive design is reasonable or not.

$$R = (K/V)^{1/\alpha} \cdot Q^{1/3} \tag{15}$$

where Q is the explosive amount, V is the security allowable particle vibration velocity at the location of the protection object; K and α are the coefficient and attenuation index related to the terrain and the geological conditions between the blasting point and the protected object.

4.3. Establish conditional probability tables (CPT)

As described in the chapter 2.4, the cloud droplet is converted to the conditional probability tables (CPT) by Eq (10), the CPT as shown in Table 5 (due to the large number, only part of it is listed).

Table 5. Conditional probability table.

X_4	X_5	X_6	X_7	B_2			
				I	II	III	IV
I	I	I	I	1.00	0.00	0.00	0.00
I	I	I	II	1.00	0.00	0.00	0.00
I	I	I	III	0.99	0.01	0.00	0.00
I	I	I	IV	0.99	0.01	0.00	0.00
I	I	II	I	1.00	0.00	0.00	0.00
I	I	II	II	1.00	0.00	0.00	0.00
I	I	II	III	0.97	0.03	0.00	0.00
I	I	II	IV	0.86	0.14	0.00	0.00
I	I	III	I	0.99	0.01	0.00	0.00
I	I	III	II	0.98	0.02	0.00	0.00
I	I	III	III	0.87	0.13	0.00	0.00
I	I	III	IV	0.62	0.38	0.00	0.00
I	I	IV	I	0.90	0.10	0.00	0.00
I	I	IV	II	0.74	0.26	0.00	0.00
I	I	IV	III	0.51	0.49	0.00	0.00
I	I	IV	IV	0.06	0.94	0.00	0.00
I	II	I	I	1.00	0.00	0.00	0.00
I	II	I	II	0.94	0.06	0.00	0.00
I	II	I	III	0.88	0.12	0.00	0.00
I	II	I	IV	0.59	0.41	0.00	0.00

4.4. Calculation of collapse risk value

(1) Weight of the first level risk factors

This article uses the ANP method to calculate the weights of the second-level indicators. The structure of ANP has two layers: the control and the network layers. The relationships between the selected risk indicators at tunnel construction sites are outlined in the ANP structure model, as shown in Figure 7. (B_i (i = 1,2…,7) are the first-level indicators, and X_i (i = 1, 2...,24) are the second-level indicators.) The judgment matrix was constructed with a super-decision-making (Super Decisions) software developed by Rozann Satty and William Adams based on the theory of ANP [29]. Each risk factor's weight is given in Table 6.

Table 6. The weights of risk factors for tunnel collapse.

First-level indicators	Weight	Second-level indicators	Weight
Drilling and blasting operations(B_1)	0.02167	Drilling(X_1)	0.00031
		Overbreak or underbreak(X_2)	0.00763
		Dangerous stone removal(X_3)	0.01373
Initial support(B_2)	0.01419	Advance support(X_4)	0.00168
		Vertical arch spacing(m) (X_5)	0.00031
		Laying steel mesh(X_6)	0.00763
		Shotcrete thickness(cm) (X_7)	0.00458
Secondary lining(B_3)	0.03357	Laying a waterproof layer(X_8)	0.00610
		Tying secondary lining steel bars(X_9)	0.01221
		Pouring secondary lining concrete(cm) (X_{10})	0.01526
Bad hydrogeology(B_4)	0.37583	Rainfall(mm)(X_{11})	0.18312
		Groundwater level(X_{12})	0.09377
		Surface water leakage(X_{13})	0.09894
Bad engineering geology(B_5)	0.41353	Integrity degree (X_{14})	0.16276
		Weak structural plane(X_{15})	0.12869
		Special soil(X_{16})	0.12208
Field exploration(B_6)	0.09849	Geological Prospecting(X_{17})	0.05395
		Advanced geological forecast(X_{18})	0.03252
		Monitoring measurement(X_{19})	0.00700
		Surrounding rock grade (km/s)(X_{20})	0.00501
Construction design plan(B_7)	0.04273	Excavation method(X_{21})	0.00305
		Excavation span (m)(X_{22})	0.01221
		Tunnel depth (H/m) (X_{23})	0.00916
		Blasting parameter selection(X_{24})	0.01831

(2) Risk loss level determination

The risk loss will be scored by five indicators (Casualties(C_1), Economic losses(C_2), Construction period losses(C_3), Damage to the surrounding environment(C_4), Loss of social reputation(C_5)). This article is mainly based on the "Code for risk management of underground works in urban rail transit" (GB50652-2011) to classify the loss level (I~V) after the risk accident.

Industry experts will be invited to determine the weights of five risk loss indicators and score the risk loss of risk factors. The final total risk loss of risk factors is the weighted sum of five indicators and can be expressed by Eq (16). The total risk loss value of the first level indicator is shown in Table 7.

$$C = \sum_{i}^{5} C_i \bullet \eta_i \tag{16}$$

where η_i is the weight of the risk loss indicator.

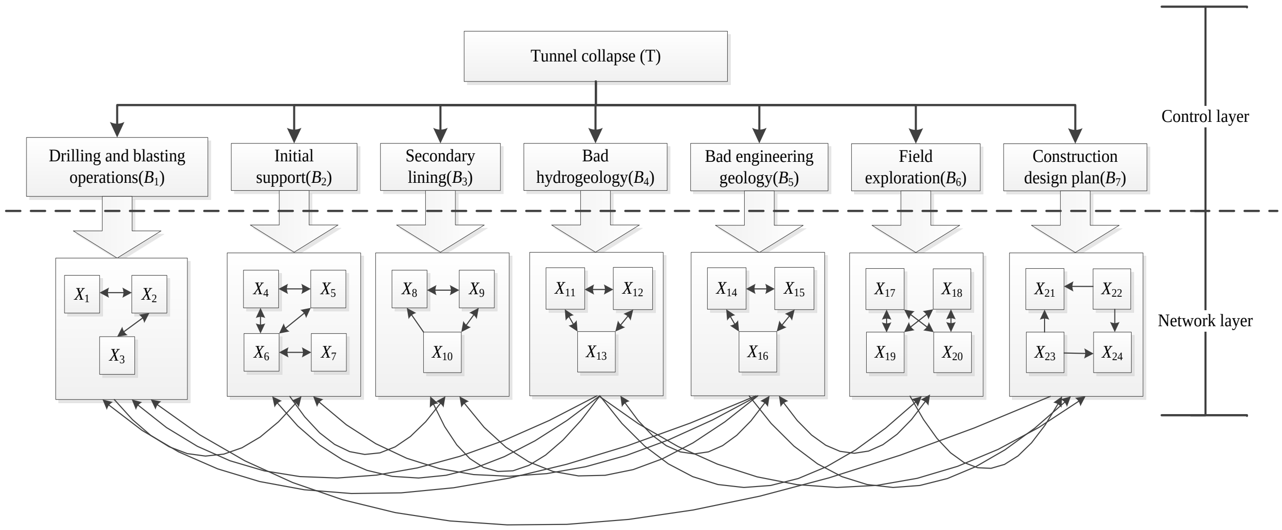

Figure 7. ANP structure model for risk factors of the tunnel collapse.

Table 7. The value of total risk loss.

First-level indicators	B_1	B_2	B_3	B_4	B_5	B_6	B_7
Risk loss (C)	3.05	1.4	1.4	2.95	2.35	1.25	2.55

Table 8. Time node table of bridge descending station.

	Sub-project	Duration（hour）	Total time（hour）
1	Preparation stage (cross-section cleaning)	1	1
2	Drill and blast completed	5	6
3	Dangerous rock removal	2	8
4	Tap slag	5	13
5	Vertical steel arch frame (including hanging steel mesh)	5	18
6	Advance support, anchor rod	3	21
7	Shotcrete	7	28
8	Invert construction	10	38
9	Concrete curing	1	39
10	Monitoring measurement	30	69
11	Laying a waterproof layer	12	51
12	Second liner steel	8	59
13	Second lining concrete pouring	10	69

(3) Exposure degree calculation

To calculate the exposure degree, we need to know the entire construction time. The entire construction time node of tunnel excavation is divided according to the process, as shown in Table 8.

One cycle of tunnel excavation is 69 hours (from the drilling and blasting to completion of the second lining), and it is divided into 13 parts. For the convenience of calculation, the concrete curing time is set to 1 hour. Taking the construction time as the universe, the fuzzy subset is each risk event, and the membership degree of the fuzzy subset is the exposure degree. Taking time as the abscissa, trapezoidal fuzzy numbers (Eq (3)) are used to establish the membership function of risk events concerning time. This means that the degree of influence of risk factors on tunnel collapse will change over time. The trapezoidal membership function parameters of each risk factor are shown in Table 9.

Table 9. Trapezoidal membership function parameters of risk events.

Second-level indicators	a	b	c	d
Drilling(X_1)	0	1	6	8
Overbreak or underbreak (X_2)	1	6	21	28
Dangerous stone removal (X_3)	1	1	8	13
Advance support (X_4)	1	6	21	28
Vertical arch spacing (X_5)	13	18	21	28
Laying steel mesh (X_6)	18	21	21	28
Shotcrete thickness (X_7)	18	21	28	31
Laying a waterproof layer (X_8)	31	39	51	56
Tying secondary lining steel bars (X_9)	50	51	59	59
Pouring secondary lining concrete (X_{10})	58	59	69	69
Rainfall (X_{11})	1	6	51	69
Groundwater level (X_{12})	1	6	51	69
Surface water leakage (X_{13})	13	18	51	69
Integrity degree (X_{14})	1	6	18	21
Weak structural plane (X_{15})	1	6	18	21
Special soil (X_{16})	1	6	21	28
Geological Prospecting (X_{17})	1	6	21	28
Advanced geological forecast (X_{18})	1	6	8	13
Monitoring measurement (X_{19})	38	38	56	67
Surrounding rock grade (X_{20})	1	6	56	67
Excavation method (X_{21})	1	6	8	13
Excavation span (X_{22})	1	6	56	67
Tunnel depth (X_{23})	1	6	56	67
Blasting parameter selection (X_{24})	1	1	6	13

5. Discussion

According to the actual observation of the risk factors, the risk assessment model can be used as a real-time decision-making tool by updating the status of the risk factors. The risk assessment values can provide real-time and effective construction security support to decision-makers. The corresponding collapse risk status of the risk value is shown in Table 10.

Table 10. Risk rating table.

Level	Risk value	Explanation
I	$20 \le R$	Precautions must be taken at all costs to reduce risks
II	$15 \le R < 20$	Identify and implement preventive measures to reduce risks
III	$10 \le R < 15$	Risks are on the verge of tolerance, preventive measures may be required
IV	$1 \le R < 10$	The risk is tolerable and no other measures are required

5.1. Pre-construction control

Decision-makers do not have an in-depth understanding of the realities associated with project risks prior to construction. Although they are told that there is a serious risk of the tunnel collapse, they have no pathway to realize the actual situation of the potential risk, let alone safety. The purpose of pre-construction control is to know in advance which works period has the highest collapse risk value. The construction party can know the risk factor with the largest impact factor in each period. Therefore special attention and corresponding measures can be taken to reduce the risk of collapse. The tunnel section at fault zone L2 was assessed by the proposed risk assessment method. A construction cycle was evaluated and the results are shown in Figure 8.

As shown in Figure 8, the collapse risk value can be divided into two stages. The first stage is 6–18 hours, which corresponding to the installation of vertical steel arches from the drilling and blasting. The risk values of this segment are all greater than 20 (a high risk of collapse). As the construction section is in the broken fracture zone, the surrounding rock is loose and more prone to a tunnel collapse. After the initial support is completed, the collapse risk value is reduced to about 10 (low-risk state). After laying the waterproof layer, the collapse risk value gradually approached zero. The results are consistent with the actual conditions of on-site construction, which proves the feasibility of the method and its application potential.

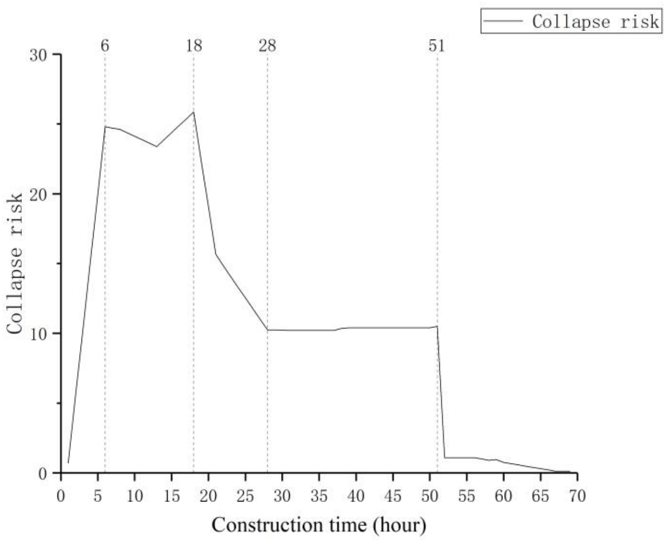

Figure 8. Collapse risk value of the entire process at Yutangxi tunnel.

5.2. During-construction control

The dynamic evaluation during construction always aims to control the risk of collapse to ensure the safety of construction. In the construction phase, decision-makers judged 24 factors (X_1-X_{24}) based on the actual situation on-site, and then entered the current states (I, II, III, or IV) into the model as given evidence. When the collapse risk value was greater than level III, the construction should be immediately suspended for rectification. The evaluation will be conducted again after the rectification. The construction will not start until the risk level was lower than level II. In this way, the construction can be continuously optimized until the high potential safety risks can be controlled.

In order to demonstrate the feasibility of the method, four testing samples are selected in the tunnel section K244+885~ K244+250, and the risk assessment results are shown in Table 11. As the collapse risk level of tunnel section No.1 is at level IV, the construction must be rectified immediately by enhancing the support conditions and timely drainage. Until the risk level is reduced to level II, construction will be carried out again. The results of the risk assessment method proposed in this paper are consistent with the actual site conditions, which demonstrates the feasibility of the method for tunnel collapse assessment.

Table 11. Tunnel collapse risk assessment result.

Tunnel section	Tunnel surrounding rock condition	Probability over Class I	Probability over Class II	Probability over Class III	Probability over Class IV	Predicted label	True label
No.1	The tunnel section is in a broken fracture zone, with more joints and fissures, the surrounding rock grade is level IV, and there are water bursts and mud.	0	0	0.18	0.82	IV	IV
No.2	The surrounding rock grade of the tunnel section is level II, and the tunnel face rock mass is complete and dry.	0.59	0.41	0	0	I	I
No.3	The surrounding rock was highly fractured and weathered siltstone and the rock surface was earthy yellow.	0.37	0.63	0	0	II	II
No.4	The surrounding rock grade of the tunnel section is level III, and there is a small amount of water seepage.	0	0.59	0.41	0	II	II

5.3. Post-accident control

The purpose of post-incident control is to identify the most likely immediate cause of an accident or failure once it has occurred. The real-time diagnosis and appropriate measures are then carried out. Under the current circumstances, the decision-makers believe that the most desirable action is to invite field experts to participate in expert group meetings. Then the field experts discuss the causes of the accident and propose prompt control measures. This is likely to miss the critical time to deal with the problem, leading to serious losses. In this research, according to the degree of membership and weight, we can simulate the evolutionary route of accidental occurrence in real-time. Taking a collapse accident of the Yutangxi tunnel as an example, this article diagnoses the accident and proposes emergency plans.

The risk of tunnel collapse was not assessed in real-time during the early stages of construction. When the tunnel face was excavated to the K244 + 995, the collapse occurred on December 19, 2019 (Figure 9). This construction section is located in the fracture zone L1. During on-site construction, the integrity of the surrounding rock mass is poor, there are many weak structural surfaces, and the surrounding rock grade is level Ⅴ. After a collapse, decision-makers needed to find the main cause and implement corresponding measures.

Figure 9. Tunnel collapse.

According to Eq (13), the risk factors that have the greatest impact on tunnel collapse are obtained (X_4, X_{11}, X_{14}, X_{15}, X_{20}). The cause of the accident can be preliminarily diagnosed, and corresponding measures can be taken. The surrounding rock grade of the excavation section is level Ⅴ, and it is in the fracture zone. Furthermore, during the construction period, it rained heavily for three consecutive days, which led to the loosening of the surrounding rocks. The support plan was not adjusted according to the site conditions, which eventually led to a collapse accident. The main reasons for the collapse are the poor surrounding rock conditions and insufficient support strength.

Therefore, the following measures will be taken: stopping excavation, backfilling, and leveling the collapsed soil of the tunnel face, and conducting shotcrete sealing. After the accident, this method provides decision-makers with timely solutions to reduce casualties and economic losses.

6. Conclusions

Tunnel construction is usually a highly complicated project associated with great potential risks. In recent years, the safety risk analysis and management of tunnel construction safety are closely related to public safety and has received extensive attention. Due to the lack of sufficient data, it is difficult to accurately estimate the possibility and loss of tunnel construction collapse. A new dynamic risk assessment method for failure analysis in tunnel construction is developed in this research. A typical hazard concerning the tunnel collapse in the construction of the Yutangxi tunnel in China is used to verify the applicability of the proposed approach. The results prove the feasibility of the method and its application potential.

With the increasing emphasis on construction safety, there is a growing need for precise failure probabilities for failure analysis in engineering management practices. To reach the highly required precision for the dynamic decision analysis, the exposure degree is proposed to ensure the reliability and timeliness of the collapse risk assessment. The nodes in the conditional probability table are multiple states, which makes the risk assessment more realistic. At the same time, the Cloud model is used to convert weights into conditional probability tables, which greatly reduces the workload of experts. Finally, through the pre-accident, during-construction, and post-accident control, the whole process of tunnel construction collapse risk assessment is realized. This method can be used as a decision support tool to guide the collapse risk analysis during tunnel construction, and it is worth popularizing in other similar projects.

The new dynamic assessment method proposed in this paper also has some limitations. At present, the weight of risk factors still relies on the subjective judgment of experts. Our subsequent research goal will focus on determining the weight of risk factors based on multiple similar tunnel projects, judging the status of risk factors by monitoring measurement data.

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Conflicts of interest

The authors declare no conflicts of interest.

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