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Original scientific paper

A Novel Subway Tunnel Collapse Risk Prediction Model using Mutation Theory

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Abstract: With the rapid expansion of urbanization, subway tunnel construction has grown significantly in scale and speed, but frequent collapse incidents pose severe risks to safety, economy, and public infrastructure. This study proposes a novel risk prediction model for subway tunnel collapse using mutation theory, which effectively captures the dynamic and discontinuous nature of collapse events. The model integrates geological, hydrological, and construction parameters and employs real-time monitoring data to achieve dynamic risk classification. Numerical simulations indicate a strong correlation between settlement, clearance convergence, and deformation, with the top settlement reaching 0.28 mm and plastic strain increasing from 1.3×10^{-4} to 1.23×10^{-3} after excavation. Case verification reveals high collapse risks at multiple monitoring points, underscoring the importance of robust monitoring and preventive strategies. The findings demonstrate that mutation theory-based risk modeling is feasible and reliable, providing a new theoretical framework and practical tool for early warning and risk management in subway tunnel construction. Future research will explore the model's applicability to diverse geological conditions and its integration with advanced monitoring systems to enhance prediction accuracy and risk mitigation.

Keywords: collapse risk estimation; geological features; hydrologic condition; mutation theory; subway; tunnel

1 INTRODUCTION

As urbanization accelerates, subway tunnels, a crucial element of urban rail transit, have seen a swift expansion in both scale and construction speed. Nowadays, collapse incidents during subway tunnel construction are becoming increasingly common, posing risks not only to the safety of workers but also resulting in substantial economic losses and significant social repercussions [1]. The emergence of collapse accidents is tightly connected to the complexity of geological conditions, limitations of construction technology, and imperfect risk assessment methods [2]. Therefore, in-depth research on the mechanism of subway tunnel collapse (TC) and the development of effective risk assessment models are of great significance for preventing and controlling TC accidents. While domestic and international researchers have delved deeply into TC problems and achieved notable advancements, there are still some areas where progress remains inadequate. The existing risk assessment methods mostly rely on empirical judgment and qualitative analysis, lacking quantitative research on the mechanism of TC, and have limited ability to assess the risk of TC in complex geological settings [3, 4]. In addition, most studies focus on emergency response and handling measures after TC, while there is insufficient research on early warning and preventive measures before collapse [5]. Therefore, there is an urgent need to develop a new theoretical framework and method to raise the accuracy and practicality of TC risk assessment.

Mutation theory is a discipline that explores the behavior of a system at its critical equilibrium point, elucidating the phenomenon of abrupt shifts triggered by gradually evolving forces or movements. Compared with traditional risk assessment methods, mutation theory can more effectively describe and predict the discontinuous behaviour of a system under small parameter changes, especially in predicting sudden disasters such as underground TC, which has a natural advantage [6]. On this basis, the study introduces an underground TC risk prediction model grounded in mutation theory, aiming to enhance the efficiency of deformation forecasting during tunnel construction. Most of the existing risk assessment methods rely on empirical judgement and qualitative analysis, and lack quantitative research on the collapse mechanism. Most of the studies rely on expert scoring and qualitative analyses, failing to fully consider the dynamic changes during the construction process. By introducing mutation theory, the study aims to remedy these deficiencies and provide a more accurate and practical risk assessment framework. The novelty of this study lies in its application of mutation theory to the risk assessment of metro TC, an area that has not been thoroughly explored in prior research. By constructing a risk prediction model based on mutation theory, it can not only predict the likelihood of TC more accurately, but also provide a scientific basis for risk management during the construction process. In addition, the study will verify the validity of the model through actual cases to further promote the application of mutation theory in the risk assessment of metro tunnel construction.

2 LITERATURE REVIEW

2.1 Applications of Mutation Theory

Mutation theory is a discipline that explores the behavior of a system at its critical equilibrium point, elucidating the phenomenon of abrupt shifts triggered by gradually evolving forces or movements. It has found broad utilization in areas like physics, engineering, and biology. Berdan E. L. et al. propose a research framework for the problem of understanding the genetic basis of different evolutionary outcomes. The understanding of different evolutionary outcomes is optimised by directly exploiting the most important feature of mutations, their population genetic effects, to determine the relative evolutionary importance of different mutation types in a given context [7]. Hu J. et al. proposed that in non-Hermitian systems with cosmic time symmetry and pseudo Hermitian symmetry, there can naturally exist more structurally rich singular swallowtail mutations to address the uniqueness problem of outliers in non-Hermitian systems, thus achieving a deeper understanding of singularity interactions and topological protection transitions in non-Hermitian systems [8]. Sáez M. et al. proposed a method that combined principled statistical methods, mutation theory frameworks, and approximate

Bayesian calculations to accurately predict cell fate decisions in developing tissues, thereby achieving accurate prediction of the fate of pluripotent stem cells under different signal factor combinations [9]. Moayedifar A. et al. raised a risk-based approach to address the high seismic risk posed by active geology and faults in Iran. By using the total probability rule to evaluate and optimize the behavior of tunnels under different earthquake intensities, and combining it with mutation theory for deformation analysis, the seismic stability assessment of urban railway tunnels has been improved [10]. Hu W. et al. proposed a resource optimisation technique for the problem of insufficient resources in urban sludge intelligent monitoring system. Water meter data was collected by using IoT and wireless technology and resource optimisation was performed based on mutation theory [11].

2.2 Risk Assessment in Tunnel Construction

The collapse of subway tunnels is caused by various factors, including but not limited to geological conditions, construction techniques, environmental impacts, etc. By constructing a dynamic risk rating system structure and utilizing monitoring data during the construction process to achieve dynamic risk rating, the safety management level of subway tunnel construction collapse accidents can be improved. Aghbolaghi H. A. et al. conducted a sustainable assessment of tunneling projects using Dempster-Shafer evidence weighting theory. A comprehensive assessment was carried out in three dimensions, economic, social and environmental, to achieve effective monitoring of tunnel construction [12]. Zhang L. et al. carried out the optimisation of grouting material properties in order to reduce the TC risk. Different cement-sand ratios, water-cement ratios and cement admixtures were designed, and the change rule of the early strength of the optimal ratio was deduced [13]. Xie X. et al. proposed a risk assessment model based on extension theory and entropy weight theory for the common collapse problem in tunnel construction, thus achieving accurate assessment and effective control of the risk of TC [14]. Chen W. et al. proposed a new comprehensive collapse risk assessment method based on case-based reasoning, rough set theory, and uncertain metric set pair analysis theory to address the accuracy of collapse risk assessment in mountain tunnel construction. The risk environment and risk factors of TC were summarized through the AHP, thereby improving the efficiency of collapse prediction in tunnel construction [15]. Kitchah F. et al. proposed a two-dimensional numerical modeling analysis for the collapse problem of T1 tunnel, which enabled the evaluation of the loads generated within the lining system and clarified the low efficiency of the support system used [16].

2.3 Advanced Computational Models for Tunnel Collapse Risk Prediction

Sarna S. et al. addressed the problem of early prediction of rock collapse events in tunnel boring machine (TBM) operations by proposing a model using TBM and geological survey data. The identification and prediction of potential TBM tunnel collapse in rock was achieved by applying multi-layer perceptron, support vector machine and random forest [17]. Baghbani A. et al. addressed the problem of the impact of new tunnels on existing tunnels by proposing a two-dimensional model using the finite element method and combining it with an artificial intelligence approach for impact prediction. Accurate analysis of the impact of the diameter of new tunnels and spacing from existing tunnels on the deformation of soil and existing tunnels was achieved by multiple linear regression and classification regression random forest techniques [18]. Fuzzy logic and machine learning models excel in dealing with uncertainty and learning patterns from big data, and usually require a large amount of data to train the model to ensure its accuracy and generalization ability, with a high dependence on the quality and quantity of data. Mutation theory, on the other hand, has advantages in terms of theoretical depth, ability to handle small datasets, interpretability of results, dynamic system modelling, and real-time prediction.

In addition, there are still some shortcomings in the existing research. The main issues include insufficient exploration of the limitations of risk assessment methods under dynamic or complex geological conditions, and insufficiently in-depth analyses of the roles of geological, hydrological, and construction factors in TC. Geological, hydrological, and construction factors are key factors affecting TC risk. For example, changes in rock quality, such as strength and degree of fissure development, can directly affect tunnel stability. Hydrological conditions, especially changes in water level, can increase the risk of TC, as changes in water pressure may lead to a reduction in the strength of the surrounding rock. In addition, construction techniques such as blasting or grouting can have a significant impact on tunnel stability.

Therefore, a risk estimation model for subway TC is established using the Qingdao Metro in Shandong Province, China, as the research object. By analyzing the influencing factors of TC risk through mutation theory, an estimation model is established aiming to raise the prediction of subway TC risk and reduce the probability of collapse risk. The study innovatively analyzes the influencing factors of TC risk grounded on mutation theory, and further constructs a collapse risk prediction model around mutation theory.

3 RESEARCH METHODOLOGY

Firstly, an overview of the research project was introduced. Secondly, based on the theory of mutation, the factors influencing the risk of TC were determined. Finally, a TC risk prediction model based on mutation theory was established.

3.1 Project Overview

The study focuses on the tunnel between Kaifeng Road Station and Shengli Bridge Station on Qingdao Metro Line 1. The tunnel is located in the middle of a composite formation and is mainly affected by water rich sand layers and rocks. During the construction process, it faces multiple risk factors such as adverse geology and groundwater. The terrain of the tunnel has small undulations, with a ground elevation range of [3.7 m, 4.3 m]. The surrounding rock on both sides of the tunnel is classified as II-V. The geological distribution of the tunnel is represented in Fig. 1.

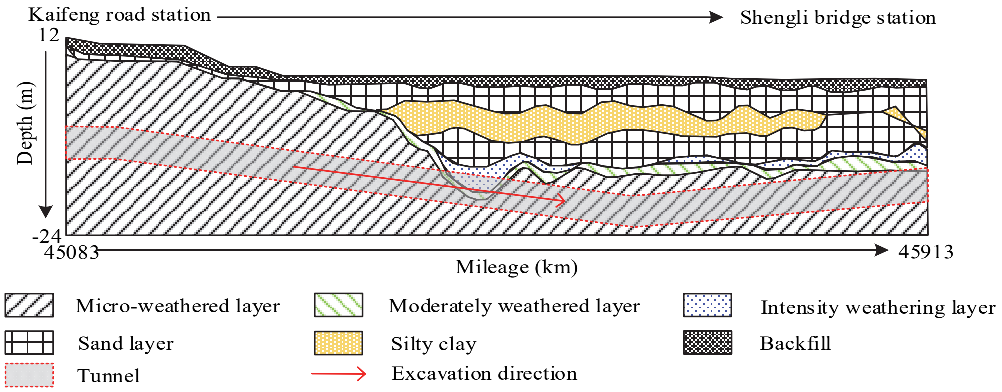


Figure 1 Study of the regional geological distribution

In Fig. 1, the main strata of the project are sand layers, silty clay, backfill soil, porphyries, tuffs, and granite. Among them, the sand layer has the largest distribution, with a thickness ranging from 1.6 m to 12.6 m, and locally contains silty clay. There is an existing tunnel with a length of 218 meters at Kaifeng Road Station, so the tunnel near Kaifeng Road Station will be constructed using the renovation method, while the remaining sections of the tunnel will be constructed using the step method. According to the step method, the tunnel section is divided into four areas, and the advanced support for the tunnel arch of the strongly weathered rock layer is a semi section advanced deep hole cement + water glass mixed grouting. The grouting parameters are represented in Tab. 1.

Table 1 Grouting section and construction length of different mileage sections

Number	Construction mileage	Construction length / m	Grouting category
1	DK45+434.01-DK45+454.01	20.00	C1
2	DK45+454.01-DK45+464.01	10.00	B1
3	DK45+464.01-DK45+509.01	45.00	A1
4	DK45+509.01-DK45+519.01	10.00	B1
5	DK45+519.01-DK45+529.01	10.00	C1
6	DK45+824.01-DK45+913.86	89.85	B1

In Tab. 1, the study divides the entire tunnel Distance Kilometer (DK) into 6 sections, with sections 1 and 5 using C1 cross-section. The grouting range is 10° from the tunnel arch top, and there are 19 drilling holes. There are 7 boreholes in Zone 1 with a single depth of 4.7 m, 7 boreholes in Zone 2 with a single depth of 7.3 m, and 5 boreholes in Zone 3 with a single depth of 5 m. Sections 4 and 6 adopt B1 cross-section, with a total of 15 boreholes, 7 boreholes in Area 1, and a single borehole depth of 7.1 m. There are 5 areas in Zone 2, with a single hole depth of 10.9 m. There are 3 areas in Zone 3, with a depth of 10.2 m. The section 3 DK adopts A1 section, with a total of 22 boreholes. There are 6 boreholes in Zone 1 with a single depth of 4.7 m, and 5 boreholes in Zone 2 with a single depth of 7.3 m. There are 6 boreholes in Zone 3 with a single depth of 11.0 m, and 5 boreholes in Zone 4 with a single depth of 10.3 m.

3.2 Analysis of Factors Influencing TC Risk Based on Mutation Theory

During the construction process, a collapse accident occurred in the area in 2019, which evolved from local water seepage on the tunnel face to tunnel and surface collapse. According to the later construction survey, the excavation by blasting method has damaged the tensile capacity of the rock, and due to the influence of rainy season rainfall, the groundwater level of the construction tunnel has increased, weakening the reinforcement ability of the surrounding rock. The collapse evolution process is shown in Fig. 2.

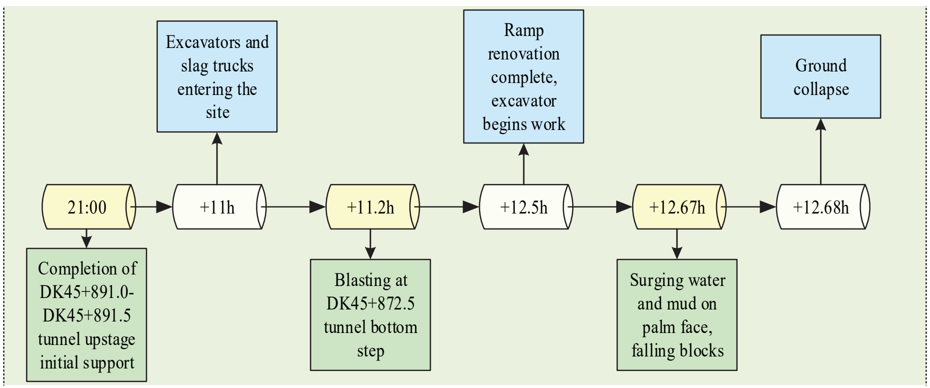


Figure 2 Study of the evolution of project collapses

In Fig. 2, 11 hours after completing the initial support of the upper steps of tunnel section DK45+891.00-DK45+891.50, an excavator and a slag transport vehicle entered the construction site, and 15 minutes later, the lower steps of tunnel section DK45+872.50 were blasted. After 1.2 hours, the slope trimming of the mileage section was completed, and the excavator began operation. After 10 minutes of homework, the tunnel face suddenly experienced water seepage, mud protrusion, and falling blocks. After 1 minute, the tunnel ground collapsed. According to the overview of the research project, the introduction of mutation theory is used to analyze the factors affecting the risk of TC. Mutation theory, as a concept that describes the mutations caused by gradually changing forces or movements, mainly addresses the phenomenon of mutations in continuous changes [19-20]. Firstly, the study assumes that the main factors causing TC are x_1, x_2,... x_n with each factor having a state variable of X_i, where $i = 1,2,......,n$. According to the theory of mutation, an energy state potential function $V(X_1, X_2, ..., X_n)$ that describes the system in different states is constructed. When the potential function reaches the critical point, the tunnel will collapse, and the specific calculation is shown in Eq. (1) [21].

$$V(X_1, X_2, ..., X_n) = \sum_{i=1}^{n} a_i X_i^2 + \sum_{1 \le i < j \le n} b_{ij} X_i X_j + \sum_{i=1}^{n} c_i X_i + d \tag{1}$$

In Eq. (1), a_i, b_{ij}, c_i, and d all represent coefficients determined by actual conditions and historical data. n represents the number of main factors. To determine the critical point of TC, the partial derivative of the potential function is calculated to be equal to 0, as shown in Eq. (2) [22].

$$\frac{\partial V}{\partial X_i} = 0, i = 1, 2, ..., n \tag{2}$$

By solving the partial derivative of the potential function, the critical point $(X_1^*, X_2^*, ..., X_n^*)$ for TC is obtained. On this basis, the mutation type of behavior near the critical point is determined. The study uses the Hessian matrix H to determine the type of mutation at the critical point of TC, as shown in Eq. (3) [23].

$$H = \begin{bmatrix} \frac{\partial^2 V}{\partial X_1^2} & \cdots & \frac{\partial^2 V}{\partial X_1 \partial X_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 V}{\partial X_n \partial X_1} & \cdots & \frac{\partial^2 V}{\partial X_n^2} \end{bmatrix} \tag{3}$$

In Eq. (3), if det(H) > 0, it indicates that the behavior of the tunnel near the critical point is stable. On the contrary, it indicates that the behavior of the tunnel near the critical point is unstable and prone to mutations. Based on the above equation and the actual situation of the research project, the influencing factors of TC risk are further studied, as shown in Fig. 3.

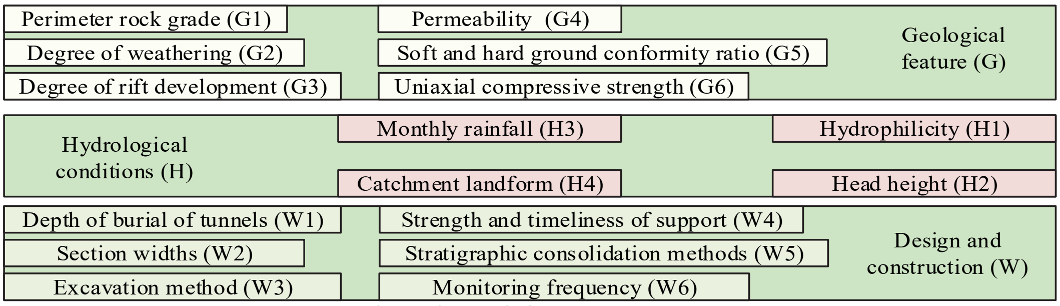


Figure 3 Influence factors of TC risk based on mutation theory

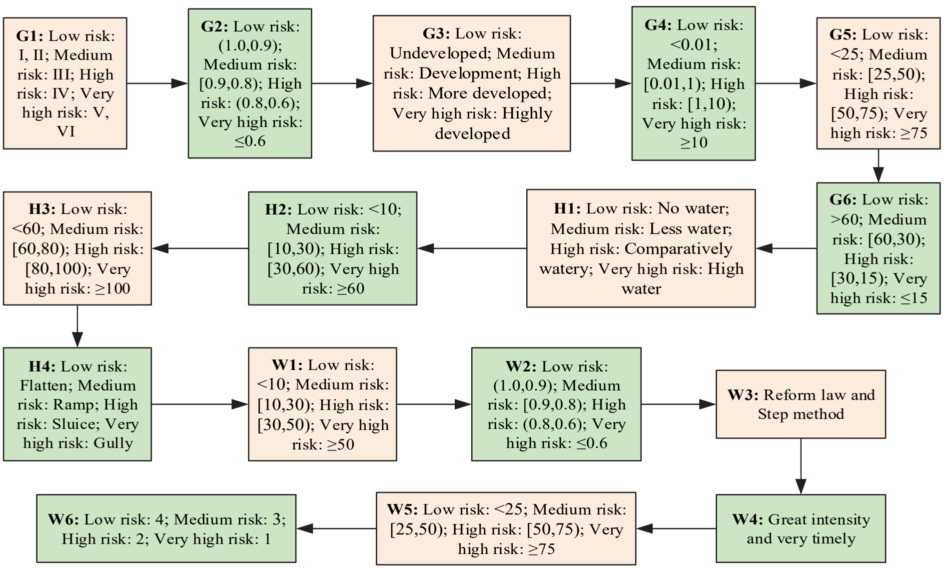


Figure 4 Risk classification of impact factors

In Fig. 3, the main influencing factors of TC can be divided into three primary indicators: geological features (G), hydrological conditions (H), and design and construction (W). Among them, geological features include the grade of surrounding rock ($G1$), geological weathering ($G2$), crack development ($G3$), permeability coefficient ($G4$), composite ratio of soft and hard strata ($G5$), and uniaxial compressive strength ($G6$). Hydrological conditions include regional water abundance ($H1$), head height ($H2$), monthly average precipitation ($H3$), and catchment topography ($H4$). Design and construction include the burial depth ($W1$), section width ($W2$), excavation method ($W3$), support strength and timeliness ($W4$), bottom reinforcement method ($W5$), and monitoring frequency ($W6$) of the tunnel. The risk level classification of each influencing factor is shown in Fig. 4.

3.3 TC Risk Prediction Model Based on Mutation Theory

Based on the elements that affect the danger of TC mentioned earlier, further research has been conducted to establish a risk estimation model for TC. Due to the various influences on the estimated object during the construction of subway tunnels, the proposed estimation model follows the following principles. The model follows the principle of integrity, and the subway tunnel safety system is composed of "geological features, hydrological conditions, and design and construction", and the system evolution process is regarded as an organic whole, with each element interdependent and mutually constrained [24]. In addition, the model follows the principles of knowability, systematicity, likelihood, similarity, and feedback [25].

Based on the above principles, a subway TC risk prediction model R_p is established on the basis of mutation theory, and the specific mathematical calculation is shown in Eq. (4).

$$R_p = p\left(G, H, W, D\right) \tag{4}$$

In Eq. (4), p represents the degree of risk occurrence. G represents geological features. H represents hydrological conditions. W represents design and construction. D represents dynamic factors. The calculation for geological feature G is shown in Eq. (5).

$$G = w_1 R_{\text{rock}} + w_2 W_{\text{weather}} + w_3 F_{\text{fracture}} + w_4 C_{\text{per}} + w_5 R_{\text{composite}} + w_6 S_{\text{uniaxial}} \tag{5}$$

In Eq. (5), w_1, w_2, w_3, w_4, w_5 and w_6 mean the corresponding weights, which are determined by the AHP. R_{rock} represents the quantitative index of surrounding rock grade. W_{weather} represents the quantitative index of geological weathering. F_{fracture} represents a quantitative indicator of crack development. C_{per} represents the quantitative indicator of permeability coefficient. $R_{\text{composite}}$ represents the composite ratio quantification index of soft and hard strata. S_{uniaxial} represents the quantitative index of uniaxial compressive strength. The calculation for hydrological conditions and design construction is shown in Eq. (6).

$$\begin{cases} H = w_7 \cdot A_{\text{aquifer}} + w_8 \cdot H_{\text{head}} \\ + w_9 \cdot P_{\text{precipitation}} + w_{10} \cdot T_{\text{topography}} \\ W = w_{11} \cdot D_{\text{depth}} + w_{12} \cdot W_{\text{width}} + w_{13} \cdot M_{\text{method}} \\ + w_{14} \cdot S_{\text{support}} + w_{15} \cdot R_{\text{reinforcement}} + w_{16} \cdot M_{\text{monitoring}} \end{cases} \tag{6}$$

In Eq. (6), w_7 … w_{16} represents the corresponding weight. A_{aquifer} represents a quantitative indicator of regional water abundance. H_{head} represents a quantitative indicator of water head height. $P_{\text{precipitation}}$ represents a quantitative indicator of monthly average precipitation. $T_{\text{topography}}$ represents a quantitative indicator of catchment topography. D_{depth} represents a quantitative indicator of the burial depth of the tunnel. W_{width} represents the quantitative indicator of cross-sectional width. M_{method} represents the quantitative indicators of excavation methods. $R_{\text{reinforcement}}$ represents a quantitative indicator of support strength and timeliness. $M_{\text{monitoring}}$ represents a quantitative indicator of monitoring frequency. The calculation process of dynamic factors is shown in Eq. (7).

$$D = w_{17} \cdot M_{monitor} + w_{18} \cdot E_{environment} + w_{19} \cdot I_{incident} \tag{7}$$

In Eq. (7), w_{17}, w_{18}, and w_{19} represent corresponding weights. M_{monitor} represents a quantitative indicator of real-time monitoring data. $E_{\text{environment}}$ represents a quantitative indicator of environmental changes. I_{incident} represents a quantitative indicator of emergencies. Therefore, the calculation for the risk estimation model of subway tunnels based on mutation theory can be updated as shown in Eq. (8).

$$R_p = p\left(G, H, W, D\right) = \varpi G + \zeta H + \theta W + \upsilon D \tag{8}$$

In Eq. (8), ϖ , ζ , θ , and υ represent the comprehensive weights, which are determined by AHP [26]. Based on the above, the process of the subway TC risk estimation model based on mutation theory is shown in Fig. 5.

In Fig. 5, the model first constructs a judgment matrix based on the collapse risk factors of the research project, establishes the weights of each influencing factor using the AHP method, and verifies the rationality of the judgment matrix through consistency testing [27]. On this basis, energy state potential functions describing the system in different states are constructed based on mutation theory, and the critical point of subway TC is calculated. Methods such as Hessian matrix are used to determine the type of mutation near critical points and determine the stability of the system's behavior near these critical points. Finally, an estimation model is established based on the weights and potential functions of the influencing factors, and the collapse risk of the research project is estimated.

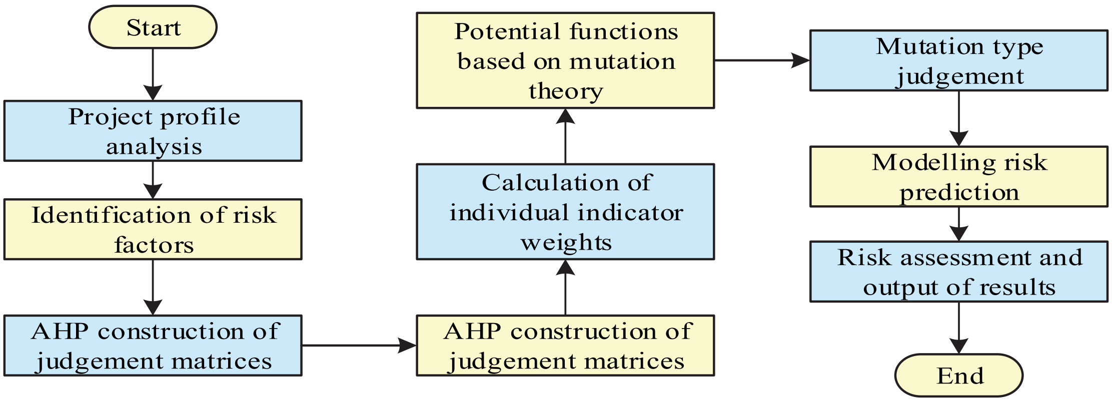


Figure 5 Model flow of underground TC risk prediction based on mutation theory

4 RESULTS AND DISCUSSION

Firstly, ABAQUS software was used for numerical simulation and analysis of subway tunnels, verifying the factors affecting TC risk and the rationality and reliability of the prediction model. Secondly, case validation was conducted to estimate the collapse risk of different DK segments.

4.1 Numerical simulation analysis of TC

To confirm the validity of the subway TC risk prediction model based on mutation theory, numerical models were used to simulate and analyze the deformation and tunnel instability during tunnel excavation. A three-dimensional numerical model of a subway tunnel measuring 80 × 72.5 × 50 m was established using ABAQUS software, and it was assumed that each layer of rock and soil in the model was made of isotropic and continuous materials with uniform texture. Meanwhile, the infiltration of groundwater in the model conformed to Forcheimer's law and did not consider situations other than saturated seepage. On the basis of the actual construction conditions of the tunnel, the step method was used to simulate tunnel excavation, and C25 concrete was used as the simulated concrete with a Poisson's ratio of 0.2 and a permeability coefficient of 8.64×10^{-5} m/d. In the boundary condition setting of the model, the upper surface was defined as an unconstrained surface. The bottom boundary was restricted by 6 degrees of activity, while on the side boundary, displacement and rotation in the X-axis direction were constrained. At the front and rear boundaries, horizontal displacement and rotation were also restricted. Based on the above simulation constraints, the study first analyzed the top settlement and net clearance convergence values of tunnel sections DK45+871.5, 45+866.5, and 45+861.5, as shown in Fig. 6.

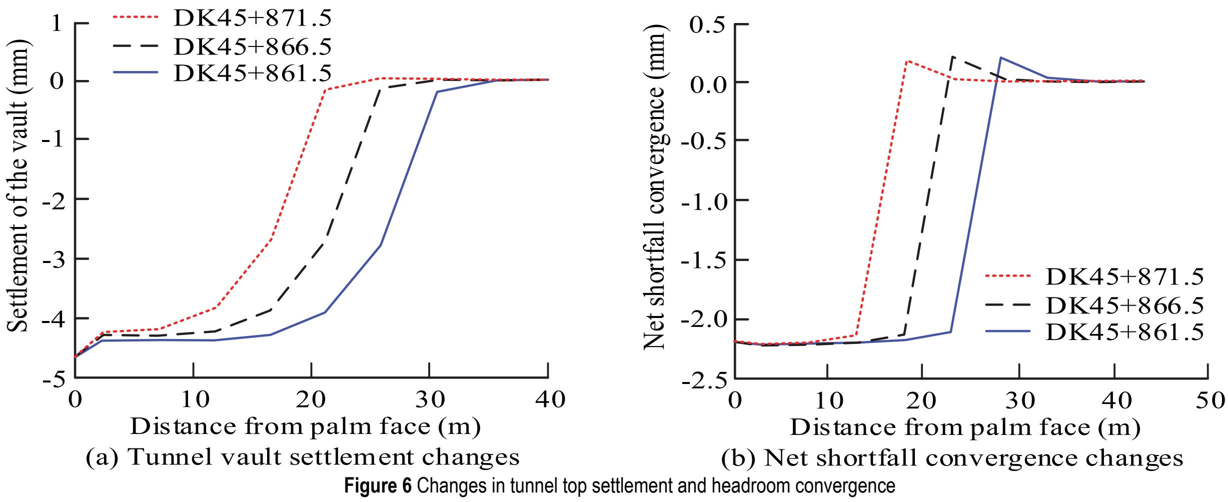
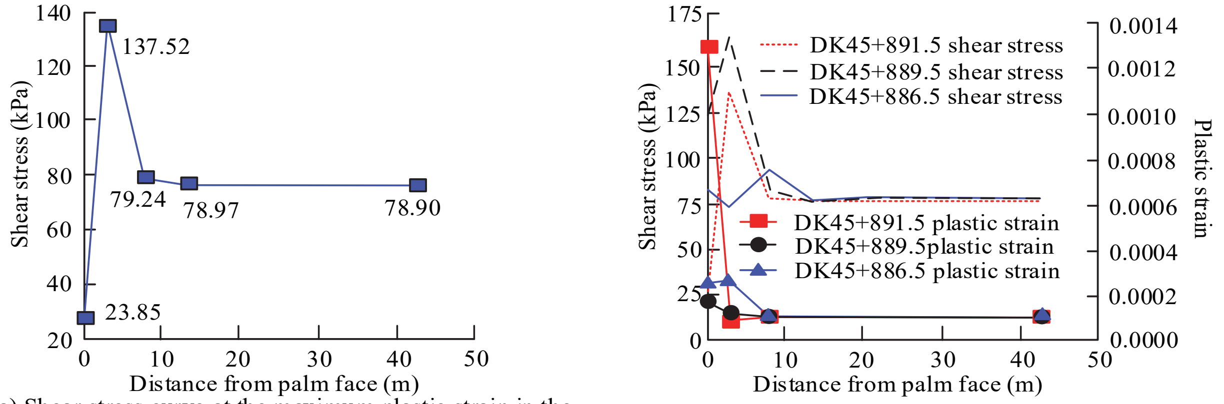


Figure 6 Changes in tunnel top settlement and headroom convergence

From the top settlement changes of tunnel section 3 DK in Fig. 6a, as the distance from the top to the palm surface increased, the top settlement of the three sections showed a trend of first increasing and then developing steadily. Among them, at position DK45+861.5, when excavating the rock mass from DK45+884 to DK45+889, the top settlement was 0.002mm. When excavating the rock mass from DK45+889 to DK45+891.5, the top settlement was 0.24 mm. When excavating the rock mass from DK45+886.5 to DK45+889, the top settlement was 0.10 mm. When excavating the rock mass from DK45+889 to DK45+891.5, the top settlement was 0.36 mm. Based on the net clearance convergence changes of the section 3 DK during excavation in Fig. 6b, the net clearance convergence of the top settlement points of different DK sections exhibited similar variation patterns. Based on on-site monitoring data, it can be demonstrated that the settlement at the top of the tunnel and the convergence of clearance were positively correlated with tunnel deformation. On this basis, the study further analyzed the impact of excavation construction on tunnel strain force, as shown in Fig. 7.



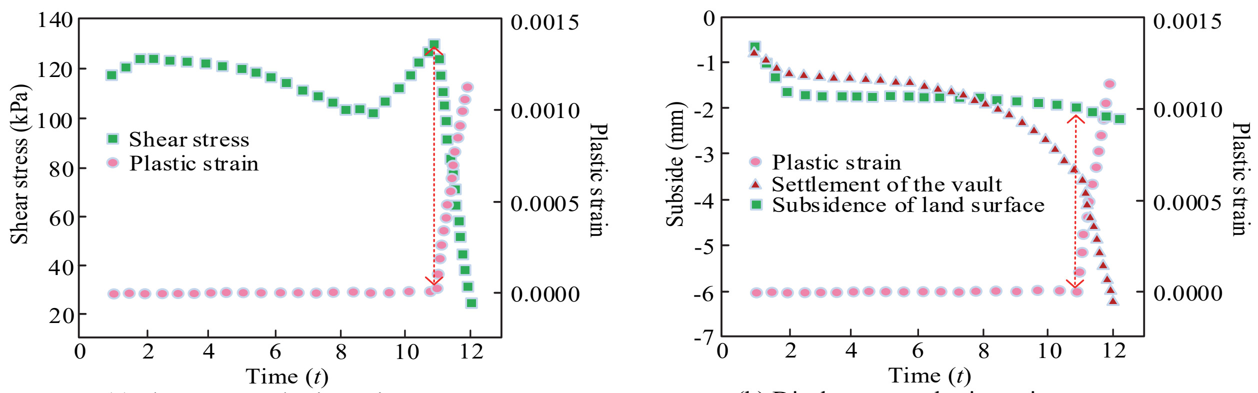
(a) Shear stress curve at the maximum plastic strain in the tunnel vault

(b) Stress-strain curve of DK section of the tunnel

Figure 7 Effect of excavation construction on tunnel strain forces

Fig. 7a gives the variation of the shear stress curve at the location where the maximum strain occurred at the top of the tunnel during excavation. It can be seen that the closer the excavation area was to the collapse area, the higher the stress at the maximum strain position at the top reached 137.52 kPa. The shear stress and plastic strain curves of DK45+886.5, 45+889.5, and 45+891.5 are represented in Fig. 7b. It can be seen that DK45+891.5, as the collapse area, had the highest plastic strain among the three DK segments, while DK45+889.5 had the highest shear stress. This may be because the DK segment was closest to the collapse area, and the collapse area had a significant impact on it. On this basis, further numerical simulations were conducted to analyze the correlation between shear stress, plastic strain, arch settlement, and tunnel seepage time in the later stage of tunnel excavation (before collapse), as shown in Fig. 8.

From Fig. 8a, after tunnel excavation, the stress of the surrounding rock of DK45+891.5 was redistributed, and the shear stress decreased from 137.25 kPa to 116.54 kPa, and continued to fluctuate to reach a new stable state. The secondary stress concentration occurred at $t = 11$, and the shear stress increased by 12.81 kPa, indicating that the surrounding rock began to undergo plastic deformation. According to Fig. 8b, the surface and arch settlement went through three deformation stages: slow ($t < 2$), stable ($2 < t < 11$), and accelerated ($t > 11$). In the early slow stage, the rock at the top of the tunnel maintained its elastic properties and did not undergo permanent deformation, while the degree of ground settlement was greater than that of the arch, which may be due to dehydration and compaction of the upper soil layer. In the stable stage, the rock still maintained elasticity, and the settlement rate of the arch was 0.226 millimeters per time unit. The ground settlement was not significant. In the later acceleration stage, some rocks began to exhibit plastic deformation, with the value of plastic strain increasing from 1.3×10^{-4} to 1.23×10^{-3}. The settlement of the arch crown increased from 3.538 mm to 6.203 mm, with a speed 12 times that of the stable stage. However, the ground settlement was still not significant. Overall, it can be seen that the rapid changes in the settlement of the arch crown were closely related to the entry of the rock into a plastic deformation state. This indicated that the grade, permeability coefficient, and uniaxial compressive strength of the surrounding rock had a significant impact on the risk of TC. Meanwhile, the research on the influencing factors of the risk estimation model determined based on mutation theory was reasonable and reliable.



(a) Shear stress-plastic strain curve

(b) Displacement-plastic strain curve

Figure 8 Shear stress, plastic strain and correlation between vault settlement and tunnel seepage time

On this basis, the study constructed a comprehensive validation framework using the leave-out method to randomly divide the collected dataset into two parts, including the training set and the test set. Among them, the training set accounts for 70% of the total data and the test set accounts for 30%. In the training phase, 5-fold cross-validation was used to assess the stability and generalization ability of the model. The training set was further divided into 5 subsets, leaving one subset as the validation set each time and the rest as the training set, cycling 5 times and calculating the average of the 5 performance metrics. The average accuracy of cross-validation was 90%, indicating that the model had good stability. At the same time, sensitivity analysis was performed on the model. The specific results are shown in Tab. 2.

In Tab. 2, the interaction between enclosure grade and regional water richness had a statistically significant effect on the predicted values of risk. Specifically, the enclosing rock grade (*G*1) in geological features (*G*) and the regional water richness (*H*1) in hydrological conditions (*H*) had the greatest influence on the predicted results of the model.

Table 2 Results of multi-factor sensitivity analyses

Enclosure class (G1)	Regional water richness (H1)	Change in risk projection / %	Interaction significance (p-value)
III	Less water	Baseline value-at-risk	-
IV	Less water	Increase 10%	-
II	High water	Increase 15%	-
IV	High water	Increase 30%	$P < 0.05$

4.2 Verification of research project examples

Based on the established TC risk estimation model, project case verification was conducted. Firstly, 10 relevant monitoring points were selected as evaluation samples in tunnel DK45+434.01-DK45+913.86, and risk estimation was carried out based on the determined collapse influencing factors. The estimated results of geological features (*G*) are shown in Tab. 3.

Table 3 Geological features (G) of TC risk prediction result

Sample number	G1	G2	G3	G4	G5	G6
1	II	0.85	Undeveloped	0.03	16.20	80.00
2	IV	0.50	Development	0.52	87.41	45.00
3	V	0.30	Highly developed	0.52	80.02	15.00
4	VI	0.30	Development	0.52	98.23	10.00
5	IV	0.70	More developed	0.00	34.48	70.00
6	V	0.30	Highly developed	5.18	69.56	15.00
7	V	0.50	Highly developed	0.00	21.80	35.00
8	V	0.50	More developed	5.18	53.84	35.00
9	VI	0.20	Development	15.00	94.12	10.00
10	V	0.40	More developed	0.10	93.75	25.00

From Tab. 3, it can be seen that the surrounding rock grades of different monitoring points in the tunnel were mostly concentrated in high-risk and extremely high-risk, and the weathering degree of monitoring points 2, 3, 4, 6, 7, 8, 9, and 10 was relatively severe. The more developed the cracks, the higher the risk of TC. Combined with the permeability coefficient, it can be further seen that the risk of TC at monitoring point 9 was extremely high. The estimated hydrological conditions (H) of 10 monitoring points are shown in Tab. 4.

Based on Tab. 4, it can be further seen that the comprehensive quantification values of hydrological collapse risk factors at monitoring points 3, 4, 6, and 9 were higher. However, tunnel design and construction, as subjective conditions, still had a positive effect on the collapse during tunnel construction. Therefore, the impact of design and construction (*W*) on the risk of TC is shown in Tab. 5.

Table 4 Hydrological conditions (*H*) of TC risk prediction result

Sample number	*H*1	*H*2	*H*3	*H*4
1	Comparatively watery	1.40	118.62	Flatten
2	High water	15.94	118.62	Flatten
3	High water	17.90	118.62	Gully
4	High water	15.88	118.62	Flatten
5	Less water	1.28	118.62	Ramp
6	Comparatively watery	3.27	57.89	Ramp
7	No water	0.11	57.89	Flatten
8	Less water	3.25	57.89	Flatten
9	High water	9.73	57.89	Ramp
10	High water	11.29	57.89	Flatten

Table 5 Design and construction (*W*) of TC risk prediction result

Sample number	*W*1	*W*2	*W*3	*W*4	*W*5	*W*6
1	16.22	7.40	Reform law	Great intensity and very timely	Pipe sheds and overruns	4
2	17.74	7.40	Reform law	Great intensity and very timely	Pipe sheds and overruns	4
3	19.00	7.40	Step method	Great intensity and very timely	Pipe sheds and overruns	4
4	16.64	7.40	Step method	Great intensity and very timely	Pipe sheds and overruns	4
5	11.60	5.20	Step method	Great intensity and very timely	Pipe sheds and overruns	4
6	11.52	5.20	Step method	Great intensity and very timely	Pipe sheds and overruns	4
7	11.00	5.20	Step method	Great intensity and very timely	Pipe sheds and overruns	4
8	10.40	5.20	Step method	Great intensity and very timely	Pipe sheds and overruns	4
9	13.60	6.40	Step method	Great intensity and very timely	Pipe sheds and overruns	4
10	16.00	6.40	Step method	Great intensity and very timely	Pipe sheds and overruns	4

According to Tab. 5, there was little difference in the estimated design and construction indicators of the 10 monitoring points in the tunnel, and overall consistency in terms of timely support strength, formation reinforcement methods, and monitoring frequency. Through comprehensive analysis of geological characteristics (*G*), hydrological conditions (*H*), and design and construction (*W*), it can be seen that the collapse risk of the tunnel near Kaifeng Road Station was at level II, and the closer it was to Shengli Bridge Station, the higher the risk level. This indicated that management personnel should strengthen the monitoring of TC during the construction process and take effective measures. Finally, in order to further illustrate the effectiveness of the model proposed in the study, the proposed metro tunnel collapse risk prediction model based on mutation theory was compared with existing models in terms of prediction accuracy and computational efficiency. Bayesian network, fuzzy logic, and machine learning based prediction models were selected for comparison. The specific comparison results are shown in Tab. 6.

Table 6 Comparison of predictive performance of different models

Model	Prediction accuracy / %	Computational efficiency / s	Sample data requirement
Bayesian network	85.01	1.21	500
Fuzzy logic	88.73	1.05	300
Decision tree	90.57	0.54	400
This paper	91.24	0.78	100

Comparing Tab. 6, the research-proposed model had a prediction accuracy of 91.24% for TC, which was significantly higher than the other three models. In terms of computational efficiency, the time required for the decision tree model was only 0.54 s, while the computational efficiency of the research proposed model was slightly higher but lower than that of Bayesian network and fuzzy logic. The research proposed model had a clear advantage in terms of data requirement. This suggested that the mutation theory model was better at capturing mutations in the state of the system, while the other models might perform better when dealing with static data.

5 DISCUSSION

The proposed mutation theory-based underground tunnel collapse risk prediction model was compared with existing models in terms of prediction accuracy and computational efficiency. The comparative analysis revealed that the mutation theory model had obvious advantages in handling small sample data and dynamic system modelling. In terms of prediction accuracy, the mutation theory model achieved an average accuracy of 91.24%, which was comparable to the machine learning model, but better than the Bayesian network and fuzzy logic model. In terms of computational efficiency, the mutation theory model was lower than the machine learning-based model in terms of computational time and resource consumption because it did not require a large amount of data training. In addition, the mutation-theoretic model outperformed other models in terms of explanatory and dynamic prediction, which was particularly important for real-time risk assessment and early warning systems.

The numerical simulation results showed that the settlement at the top of the tunnel increased from 3.54 mm to 6.20 mm, and this change was closely related to the rock entering the plastic deformation state. This settlement behaviour suggested that real-time monitoring and early warning systems should be strengthened during tunnel construction, especially in areas with low rock strength or high water pressure. In addition, the evolution of strain also suggested that the risk of collapse could be effectively reduced by increasing the reinforcement of the tunnel during the high-risk phase. These findings provided specific guidance for tunnel construction and helped optimize construction methods and improve construction safety.

The findings of the study have important practical implications for construction safety protocols and cost-effective measures. It is advisable to implement a real-time monitoring system during tunnel excavation, particularly in areas characterized by weak rock formations or elevated water pressure. In addition, based on the results of the model predictions, reinforcement measures, such as additional support or grouting reinforcement, can be taken in advance during the high-risk phase to reduce the risk of collapse. These measures not only improve construction safety, but also optimize resource allocation and reduce project costs.

6 CONCLUSION

This study proposed a novel subway tunnel collapse risk prediction model based on mutation theory, offering a dynamic and quantitative approach to risk classification. By integrating geological, hydrological, and construction parameters, the model captured the complex, nonlinear nature of tunnel collapse events. Numerical simulations demonstrated strong correlations between settlement, deformation, and plastic strain, with case validation confirming the model's applicability to real-world scenarios. These findings provided a new theoretical framework and practical tool for enhancing safety in urban rail transit projects. However, the study does have its limitations. The reliance on simulated data and a single case validation restricts the model’s generalizability to diverse geological and construction conditions. Future research should focus on validating the model with a broader range of real-world projects, incorporating advanced technologies such as AI for real-time monitoring, and adapting the model to extreme scenarios like seismic activity or water ingress. The broader implications of this work are significant. By providing early warnings of potential collapses, the model can reduce construction delays, optimize resource allocation, and improve public safety. It also offers a cost-effective solution for risk management in large-scale infrastructure projects. As urbanization continues to drive demand for subway construction, this study represents a critical step toward safer and more efficient tunneling practices.

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