

Dynamic coupling risk assessment model of utility tunnels based on multimethod fusion

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ARTICLE INFO

Keywords:

Utility tunnel
Risk coupling
NK model
System dynamics

ABSTRACT

Accidents in utility tunnels are usually caused by coupling multifactor risks, and ignoring the coupled risks can lead to biased estimates of the actual risk threats and losses. However, there are complex types of risks and coupling relationships within utility tunnels, which clarifies the coupling relationships between various types of risks and improves the accuracy of the assessment model to fit in reality. Therefore, this paper simulates the evolution process of utility tunnel risks based on the latent Dirichlet allocation algorithm, the NK model and the system dynamics to realize unbiased and accurate estimates. First, the risk factors are analyzed and classified using the latent Dirichlet allocation, and the coupling relationship is screened for employing the NK model. As a result, a system dynamics simulation model is established to determine the key risk coupling factors with the greatest impact on utility tunnels. Finally, a case study is given to illustrate the practicality and effectiveness of the model. The results show that the changes in utility tunnel risk coupling relationship can effectively characterize the changes in the dynamic risk of the utility tunnel. Moreover, the results can also be used to determine the coupling relationship that has the greatest influence on utility tunnels.

1. Introduction

Utility tunnels are underground spaces where electricity, water, communications, heating pipes, natural gas and other public services are integrated with facilities for maintenance, lifting and monitoring [1]. The utility tunnels replace the traditional practice of laying pipelines directly underground and can substantially improve the safety and life of various pipelines, greatly reducing the probability of leakage and explosion, which is an important part of modernizing urban infrastructure. The utility tunnel is a complex system with dynamic and nonlinear characteristics, which usually has complex uncertainties, such as a long construction period, a multi-technical intersection, a vicious construction environment, and crossing existing buildings or structures. Additionally, the utility tunnels will also be affected by various risk factors from the construction staff, operating environment, mechanical equipment, and construction management, which have strong interactions and domino effects [2] that are likely to cause serious coupled accidents, such as collapse, explosion, and mechanical injury. For example, a fire accident in Hong Kong in December 2020 that caused six burn injuries was an accident resulting from the coupling of three risk factors: human, environmental, and management; an explosion in Bangkok in October

2020 resulted in three deaths and 28 burn injuries due to illegal construction was an accident that coupled of two risk factors: human and management. Ignoring the coupling effect between different risk factors or the incomplete consideration of risk occurrence will lead to bias when estimating the actual risk threat and loss [3]. Therefore, measuring the interaction of multifactor coupling is the key to properly assessing the risk of utility tunnels.

Some studies have been conducted on the risk management of utility tunnels [4–8], which were mainly based on the index system formed by manual treatment of single national policies, accident reports or related literature; most studies focus on the analysis of disaster accidents within utility tunnels. Researchers have used numerical simulations or experimental methods to statically analyze the impact of a single risk factor on utility tunnel accidents [9] with less consideration of the interaction between risk factors. Additionally, the disaster-causing process of utility tunnels under the action of multiple risk factors is dynamic, and thus, the coupling effect between risk factors and the dynamic change process of risk coupling should be considered in the risk management process of the utility tunnels. The motivations are emphasized as follows: (1) The efficiency and objectivity of the risk indicator system construction need to be improved. The establishment of the current risk system is mainly

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<https://doi.org/10.1016/j.ress.2022.108773>

Received 5 March 2022; Received in revised form 2 June 2022; Accepted 21 August 2022

Available online 22 August 2022

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done manually based on single national policies, accident reports or related literature, which to a certain extent lacks the efficiency of construction and inevitably raises a problem of subjectivity in the construction process. (2) Both coupling and accurate effects between risk factors should be considered in risk management. Most studies on utility tunnel risk management focus on the analysis of disastrous accidents within the utility tunnels. Moreover, researchers have used numerical simulations or experimental methods to statically analyze the impact of a single risk factor on utility tunnel accidents with less consideration of the interaction between the risk factors. In addition, there are many types of risks and complex coupling relationships in utility tunnels. If some unexpected uncertainties occur, the risk performance can be affected, which means excessive factor computing can hinder the analysis of the model and the practical meaning. (3) Lack of consideration of dynamic models for multifactor conditions. Most of the research on the risk of utility tunnels mainly uses numerical simulations or experimental methods to analyze the impact of a single risk factor on utility tunnel accidents to determine the degree of emergency of the accident. In fact, most accidents, such as collapses and fires in utility tunnels, are influenced by multiple factors, which change with time and environmental conditions, i.e., the disaster-causing process is dynamic according to the action of multiple factors.

Therefore, this paper describes constructing a dynamic coupling risk assessment model for utility tunnels with data from the literature and accident reports related to utility tunnels. Specifically, the model first uses the latent Dirichlet allocation (LDA) algorithm for text analysis, and then constructs a utility tunnel risk index system, before developing the NK model to accurately measure the coupling degree of the utility tunnel risk. Finally, we establish a system dynamics model to simulate the dynamic evolutionary path of multi-risk coupling in the utility tunnel. This paper illustrates the practicality and the effectiveness of the model through an application example, which can provide a certain decision basis for utility tunnel risk management and enable managers to assess the risks of utility tunnels and plan risk treatment actions more effectively.

The contributions of this paper are as follows: (1) Reasonable construction of a risk index system. This paper combines the LDA algorithm in the construction of a risk index system, which can improve the efficiency of the large-scale analysis of the collected literature and accident reports. LDA can realize the automatic mining of textual topics without relying on manual identification of the corpus, which reduces the subjectivity in the construction of the index system to a certain extent. (2) Accurate measurement of risk coupling. This paper considers the coupling effect between risk factors in the risk management of utility tunnels and uses the NK model for risk coupling metrics based on the selected two Level I risk factors with the strongest coupling relationship. Additionally, reducing the complexity of the model can improve the model's accuracy for risk coupling metrics. (3) Dynamic evolution process of risk coupling. On the basis of the coupling degree measurement results of the NK model, the two Level I risk multi-factors with the largest coupling degree are selected and the dynamic evolution process of the utility tunnel risk is simulated by constructing cause and effect relationships between factors and corresponding functional equations, which can provide some decision basis for utility tunnel risk management. The model in this paper has the following advantages: (1) it is more efficient and objective in terms of risk system construction; (2) it has a more intuitive coupling relationship and degree of action in coupling degree measurement; and (3) it has less model complexity while accurately measuring dynamic risk coupling.

The remainder of this paper is organized as follows. Section 2 is the literature review. The proposed approach is described in Section 3. Section 4 depicts the modeling process to provide an example of a utility tunnel, including the definition of the model's structure and a description of the parameters. Section 5 presents the results and discussion. Section 6 is the conclusion of the paper.

2. Literature review

Research on risk coupling has become a common topic of interest for researchers involving various fields, such as rail transportation, geohazards, and aviation and navigation, though the research methods for risk coupling vary from field to field. Therefore, this section analyzes the research fields and methods of risk coupling separately to provide a reference for the research of risk coupling in utility tunnels.

2.1. Current status of risk coupling research

Risk coupling refers to the different types of risks that are spread along the risk chain and interact with other types of risks, thus changing the original risk status and causing risk managers to make biased estimates of the actual risk. Qiao classified coupling risks into single-factor coupling, two-factor coupling and multifactor coupling according to the number of factors involved [10]. The research on risk coupling has covered various areas. Moradi et al. proposed a novel mathematical architecture for the operational status and risk monitoring of complex engineering systems (CES) by conducting a case study of a real world vapor recovery unit on an offshore oil production platform [11]. Ming et al. developed a quantitative multi-hazard assessment framework for a compound flooding risk that enabled the analysis of hazard interactions and interdependencies [12]. Ruiz-Tagle et al. constructed a risk assessment model for third-party excavation damage in natural gas pipelines [13]. Fu et al. analyzed the interaction of safety risks in deep foundation pit projects in subways [14].

Research on risk coupling is mostly applied in the fields of rail transportation, geological hazards, aviation and navigation, etc. At this stage, the research on the coupling form, the coupling mechanism, the action law and the decoupling principle of risk coupling has been achieved in stages, and different methods and models can be applied to various fields to study the coupling mechanism and the coupling degree of risk, but the research on risk coupling in the field of utility tunnels is not comprehensive enough.

2.2. Risk coupling assessment methodology

Most of the scholars' research on risk coupling is applied in the fields of rail transportation, engineering projects, aviation and navigation, etc. They are able to apply different methodological models to various fields. Fu et al. developed a modeling framework and analysis procedure for risk interaction based on association rule mining and weighted network theory to analyze risk coupling in a deep foundation pit project [14]. Li et al. introduced a new Monte Carlo simulation-based risk interdependence network model to develop a hierarchical project risk interdependence network based on the identified risks and their causal relationships [15]. Zhao et al. combined complex networks with multicriteria decision analysis (MCDA) to assess multifacility risk chains and coupling in urban underground spaces [16]. Liu et al. proposed a novel method to quantify the risk coupling of subsea blowout accidents based on a dynamic Bayesian network (DBN) and the NK model [4]. Chen et al. developed a hybrid method integrating system dynamics (SD) and Monte Carlo (MC) simulation to assess the vulnerability of subway systems in operation from a long-term perspective [17]. Wang et al. proposed a novel method to improve the conventional failure mode and effect analysis (FMEA) for risk assessment based on the consideration of risk interactions and propagation effects [18].

At the present stage, the assessment method for risk coupling is mainly static analysis, primarily using numerical simulations or experimental methods to analyze the impact of a single risk factor. However, the disaster-causing process of the utility tunnel according to the action of multiple risk factors is dynamic, and the dynamic evolution process of risk coupling of the utility tunnel should be analyzed. In addition, before risk assessment, the construction of the risk system is mostly based on national policy, accident reports and related literature on human

combing in summary; there is often a strong subjectivity and the scientific nature is relatively low.

In summary, this paper analyzes and simulates the dynamic evolution process of risk coupling of utility tunnels, the constructed a risk index system of utility tunnels by using the LDA algorithm, measures the risk coupling degree of utility tunnels by using the NK model, and finally, conducts a simulation study of system dynamics to simulate the dynamic evolution risk coupling process of utility tunnels. The proposed model can provide a decision basis for utility tunnel risk management and enable managers to evaluate the risk of utility tunnels and plan risk treatment actions more effectively.

3. The model

3.1. The proposed model

The proposed model is shown in Fig. 1. First, the literature and accident reports with the keyword "utility tunnel risk" are analyzed using the LDA algorithm to determine the types of risk factors [19]. Second, the coupling degree value is calculated by the NK model to filter out the two-factor coupling relationship with the highest coupling degree. Third, expert interviews are conducted, and the risk interaction strength between the hierarchical risk and the bottom sub-risks is calculated. Based on these results, a system dynamics simulation model is established to simulate the risk coupling of the utility tunnel by establishing the causal relationship between factors and constructing the corresponding functional equations to determine the key factors of risk coupling that have the greatest impact on the utility tunnel.

3.2. The LDA algorithm and risk factor selection

3.2.1. The LDA algorithm

LDA is an unsupervised machine learning algorithm proposed by Blei et al. to identify and extract thematic information from large-scale text. The LDA transforms each text into a corresponding word frequency vector, which means that the text information is transformed into numerical information that can be easily modeled. The document can be regarded as a probability distribution of topics and the topics are probability distributions of word items with the following probability equation [20].

$$p(\varphi, \theta, Z, W | \alpha, \beta) = \prod_{k=1}^K p(\varphi_k | \beta) \prod_{m=1}^M p(\theta_m | \alpha) \left(\prod_{n=1}^N p(Z_{m,n} | \theta_m) p(W_{m,n} | \varphi_{Z_{m,n}}) \right) \quad (1)$$

where β and α are the Dirichlet parameters; θ_m denotes the topic distribution of the m^{th} document; φ_k denotes the word distribution of the k^{th} topic, which obeys the Dirichlet distribution, i.e., $\varphi_k \sim Dir(\beta)$, $\theta_m \sim Dir(\alpha)$; $Z_{m,k}$ denotes the k^{th} topic of the m^{th} document; and $W_{m,n}$ denotes the n^{th} word of the m^{th} document. The only parameter that can be observed in the model is $W_{m,n}$, and the posterior distribution of the other parameters are calculated with the help of the W parameter. Fig. 2 represents the graphical model of LDA.

In this paper, we implement LDA topic modeling with the help of Python. First, we calculate the perplexity of the LDA model to determine the number of topics, and on this basis, we analyze the related literature and accident reports of utility tunnels to establish a risk index for utility tunnels.

3.2.2. Risk factor selection

According to the reports of production safety accidents in housing and municipal engineering published by the Ministry of Housing and Construction of China and the news of the accidents in utility tunnels on Google and Sohu, a total of 75 reports of major accidents in utility tunnels were collected from 2013 to 2022. Most of the accidents were located on city streets, causing millions of dollars of asset damage and most were accompanied by casualties. In addition, we extracted literature from China National Knowledge Infrastructure (CNKI) and ScienceDirect with the keyword "utility tunnel risk."

The literature and accident reports were analyzed by the LDA algorithm to construct the risk indicators of human and environmental factors in utility tunnels. Fig. 3 shows the perplexity of the LDA model; the lower the perplexity is, the higher the accuracy of the model. Therefore, this paper selected 4 topics for topic extraction. Table 1 shows the extraction results for the LDA topics.

Table 1 shows that Topic 1 is about environmental risks, including natural disasters, such as earthquakes and rainstorms, damage to the utility tunnel from surrounding construction, temperature and humidity effects inside the pipeline, harsh working environments for employees,

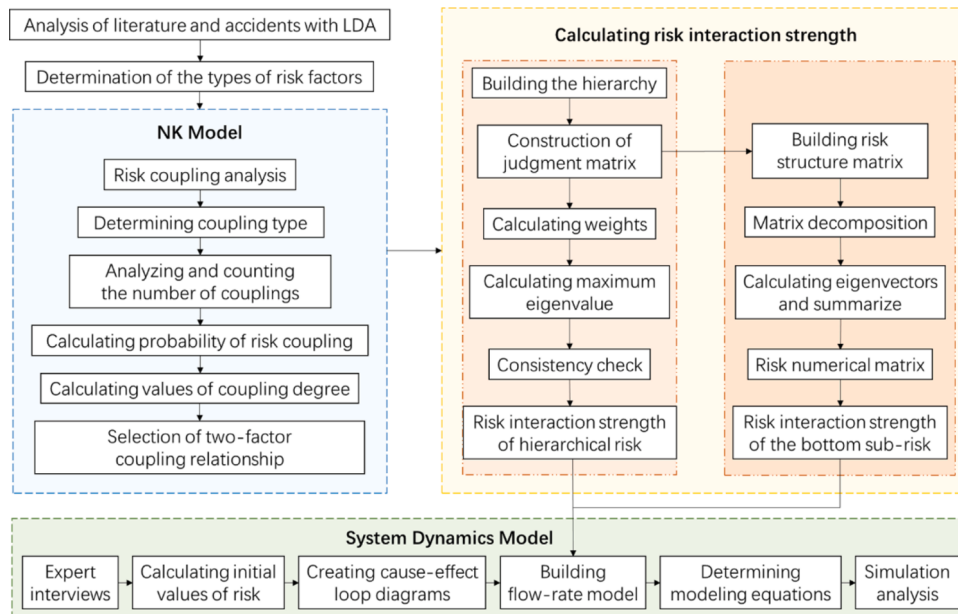


Fig. 1. The proposed model.

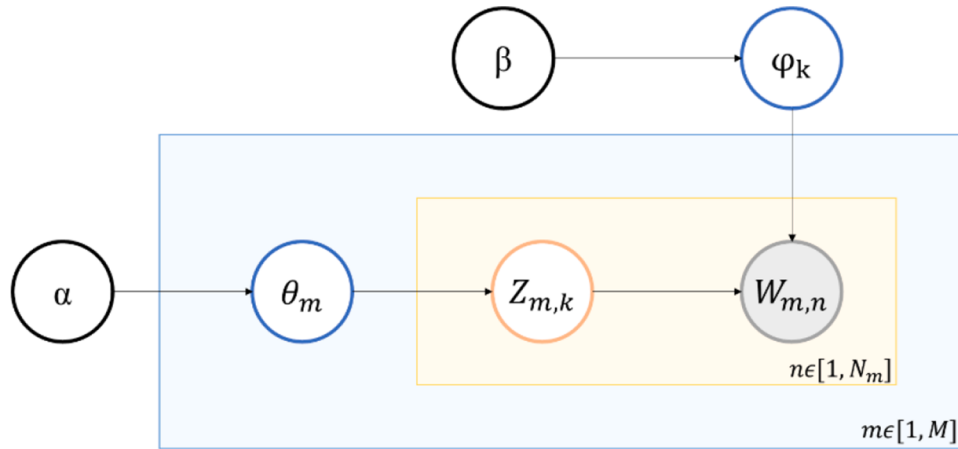


Fig. 2. Graphical representation of LDA.

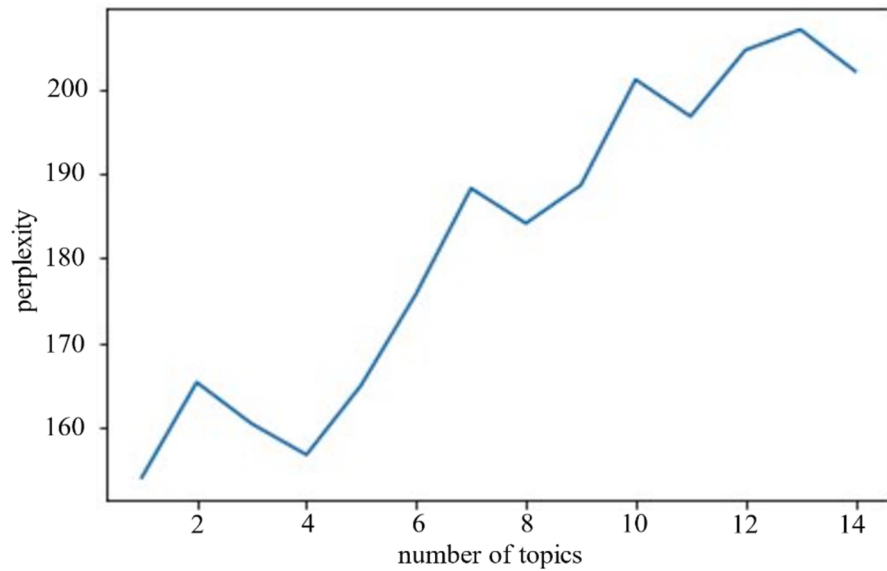


Fig. 3. The perplexity of the LDA model.

Table 1
LDA topic extraction results.

Topic 1	Topic 2	Topic 3	Topic 4
Environment	Failure	Management	Specialty
Gas	Equipment	Production	Physiology
Natural disaster	friction	Training	Psychology
Temperature	Aging	Education	Abilities
Earthquake	Design	Regulations	Personnel
Rainstorm	Inspection	Supervision	Safety
Surrounding	Protective	Violations	Emergency
construction	devices	response	response
Harsh	Machine	Skills	Awareness
Humidity	Procedures	Construction	Competence
Intrusion	Losses	Illegal	Work

and external intrusion. Topic 2 indicates equipment risks, including aging and wear of equipment, poor design, untimely inspection, and inadequate configuration of protective devices. Topic 3 describes topics related to management risks, including inadequate regulations, unreasonable supervision means, and insufficient training and education. Topic 4 is about human risks, including inadequate technical expertise, physical discomfort, insufficient psychological quality and emergency response capability, and low awareness of safety production.

3.3. Dynamic coupling risk assessment multimethod

3.3.1. The NK model

The NK model of Kauffman and Weinberger was used to study gene systems in evolutionary biology [21], and initially applied to solve gene combination problems before evolving to a structured simulation method suitable for studying the influence of the interaction between elements within a system on the overall adaptability of the system.

For the NK model, there are only two important parameters in the model, N and K . The value of N directly affects the range of K , i.e., $0 \leq K \leq N-1$, and when $K=0$, the system properties depend on the properties of each type of element itself; when $K>0$, the system properties depend on the properties of each type of element itself, as well as the influence of other elements; when K reaches a certain degree, the relationship between the group elements can form a network. By calculating the value of the coupling degree between risk factors in the overall system of the utility tunnel, the degree of influence of the coupling between risk factors on the system can be evaluated. In general, the greater the number of couplings, the higher the probability of the coupling, and the larger the risk of the coupling, the higher the probability of an accident. The application of the model is based on historical data statistics of the utility tunnel, and the data calculation is used to determine the internal factors of the system correlation and the degree of impact

determination. The calculation equation is as follows.

$$T(r_1, r_2 \dots r_N) = \sum_{I_1=1}^n \dots \sum_{I_N=1}^n (P_{I_1, I_2 \dots I_N} \log(P_{I_1} \cdot P_{I_2} \dots P_{I_N})) \quad (2)$$

where $r_1, r_2 \dots r_N$ denotes the N class of risk factors; $P_{I_1, I_2 \dots I_N}$ denotes when r_1 is in the I_1 state, r_2 is in the I_2 state...and r_N is in the I_N state and the probability of the occurrence of the risk coupling of N types of factors, the higher the calculated T value.

3.3.2. Determining the risk interaction strength

The relationships between the utility tunnel risks can be divided into two types: hierarchical risks and bottom sub-risks. The risks between hierarchical risks must interact with each other. For example, a Level I risk will be affected by all its corresponding sub-risks (Level II risk). However, there is not necessarily an interaction relationship between bottom sub-risks, which requires further analysis and determination.

1 Risk interaction strength of hierarchical risk

The relationship between the hierarchical risks of the utility tunnel is that all sub-risks are associated with their corresponding higher-level risks. For example, in the risk management process of the utility tunnel, the Level I risk factors R_i are all associated with the overall risk R of the utility tunnel, and the Level II risk factors R_{ij} are all associated with the Level I risk factors R_i . The corresponding risk factors were processed by experts in interviews according to hierarchical logic to obtain the weights of risk factors. The experts were interviewed by a questionnaire using the nine-level scale of risk intensity [22] and the collected questionnaire data were processed to form a judgment matrix. The maximum eigenvalues (λ_{max}) and the eigenvectors of the judgment matrix were calculated and the consistency test was performed.

To simplify the calculation process, Python was used to calculate the eigenvectors of the judgment matrix and perform the consistency test. The consistency ratio (CR) is compared with 0.1; when $CR < 0.1$, the judgment matrix passes the consistency test, and its eigenvector can be used as the weight of the degree of influence of the sub-risks on the corresponding higher-level risk.

1 Risk interaction strength of the bottom sub-risks

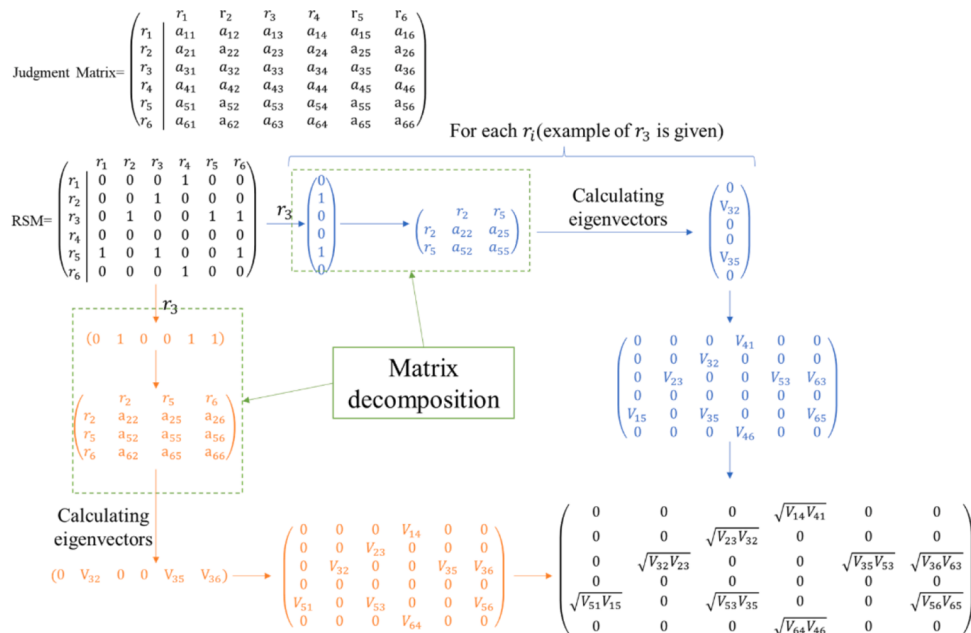


Fig. 4. Calculation of the interaction strength between the bottom sub-risks.

Marle developed a method to obtain the risk interaction strength of the bottom sub-risks [23] that can determine the strength of the interaction between the bottom sub-risks of a utility tunnel, as shown in the illustration of the process in Fig. 4.

First, a judgment matrix and a risk structure matrix (RSM) are obtained after expert interviews for all the bottom sub-risks of the utility tunnel [23]. RSM is a binary and square matrix; when $RSM_{ij} = 1$, R_i influences R_j . Second, the matrix is decomposed to extract the rows and columns corresponding to each sub-risk with columns indicating the possible effects and rows indicating possible causes. The relative strengths are substituted between the selected factors and their related factors in the judgment matrix. The matrix decomposition is carried out as in Fig. 4, which shows R_3 as an example. Third, two new matrices are obtained after decomposition, and the new matrices are used to calculate the eigenvectors separately. Fourth, for each risk factor R_i , the resulting eigenvectors are aggregated separately to obtain two numerical matrices. Finally, since the result prefers a relatively balanced value, the geometric mean of the two numerical matrices is computed to obtain the risk numerical matrix (RNM). The value of RNM_{ij} can be regarded as the coupling coefficient between the bottom sub-risks of the utility tunnel, which provides a data basis for the construction of the system dynamics equations below.

3.3.3. System dynamics method

System dynamics (SD) can be used to qualitatively study the coupling paths of various risk factors and the dynamic response process of the risks of the utility tunnel system. System dynamics (SD) was introduced by Professor J. W. Forrester of the Massachusetts Institute of Technology (MIT) in 1956. Because of the dynamic interactions between various system components, SD is used to analyze complex system behavior by combining qualitative and quantitative information to simulate patterns of behavior [24], which means that SD can be used to qualitatively study the coupling paths of various risk factors and the dynamic response process of the risks of the utility tunnel system. It is now widely used in the socioeconomic [25], ecological [26], project management [27], logistics and supply chain [28] fields. It can solve system problems with complex nonlinear, high-order, repetitive feedback and other properties. SD is guided by the system dynamics theory and method, starting from the relationship between the internal factors of the system, the establishment of a mathematical model of the internal dynamics of the

system, and the realization of the process of the dynamic evolution of the system with the help of the relevant software. This paper selects the Vensim PLE for simulation research.

The concept of SD is presented in a simplified way through graphs and basic algebraic formulae rather than complex mathematical or numerical models [29]. A complete SD simulation model consists of two models: the causal loop diagram (CLD) and the stock-and-flow diagram (SFD) [30]. Fig. 5 shows an example of two models in the Vensim PLE software where (a) is a CLD and (b) is an SFD. The state variables are the variables of the cumulative effect in the system, indicating the system state, whose values are affected only by the rate variables. The rate variables reflect the changes of the state variables with time, while the auxiliary variables are the intermediate variables between the state variables and the rate variables. Additionally, the constants are the quantities that change little or remain relatively constant during the study period.

The operation of the system and the condition at any point in time depend on the given initial conditions and the system structure; building the SD model is equivalent to solving the $X' = f(X, U, t)$ system of differential equations. The equations for the state variables are classified as continuous or discrete.

$$lvS(t) = S(t_0) + \int_{t_0}^t rateS(t)dt = S(t_0) + \int_{t_0}^t [inflowS(t) - outflowS(t)]dt \quad (3)$$

$$lv.K = lv.J + DT(inflow.JK - outflow.JK) \quad (4)$$

where lv denotes the variable state; inflow and outflow represent the inflow rates and the outflow rates, respectively; t_0 is the initial moment, t is the current moment, DT is the calculation interval and JK is the time interval from moment J to moment K .

4. Case study

4.1. Construction of the NK model for the risk coupling of utility tunnels

The number of occurrences of various forms of risk coupling leading to accidents, as well as the frequency, is calculated by analyzing the utility tunnel accident reports, and the frequency is taken as the probability of occurrence of that form of risk coupling. Table 2 shows the calculation results, where a, b, c and d in P_{abcd} are ranked according to the human risk, environmental risk, equipment risk, and management risk, respectively. The case where the risk factor does not break through its defense system (the risk does not occur) is marked as "0", and the case where the risk breaks through its defense system (the risk occurs) is marked as "1", such that 1011 means that the risk in the system is generated by the coupling of three kinds of risks: human risk, equipment risk, and management risk.

The formulae for each form of risk coupling T value can be deduced separately from Eq. (2).

$$T_4(a, b, c, d) = \sum_{h=1}^H \sum_{i=1}^I \sum_{j=1}^J \times \sum_{k=1}^K P_{h,i,j,k} * \log_2 \left(\frac{P_{h,i,j,k}}{P_{h...} * P_{i...} * P_{j...} * P_{k...}} \right) = 0.1399 \quad (5)$$

$$T_{31}(a, b, c) = \sum_{h=1}^H \sum_{i=1}^I \sum_{j=1}^J P_{h,i,j} * \log_2 \left(\frac{P_{h,i,j}}{P_{h...} * P_{i...} * P_{j...}} \right) = 0.0555 \quad (6)$$

Similarly, we obtain $T_{32}(a, c, d) = 0.0218$, $T_{33}(a, b, d) = 0.0325$, and $T_{32}(a, c, d) = 0.0520$.

$$T_{21}(a, b) = \sum_{h=1}^H \sum_{i=1}^I P_{h,i} * \log_2 \left(\frac{P_{h,i}}{P_{h...} * P_{i...}} \right) = 0.0252 \quad (7)$$

In addition, we also obtain $T_{22}(a, c) = 0.0107$, $T_{23}(a, d) = 0.0032$, $T_{24}(b, c) = 0.0135$, $T_{25}(b, d) = 0.0024$, and $T_{26}(c, d) = 0.0024$.

From the above calculation results, we know that $T_4 > T_{31} > T_{34} > T_{33} > T_{21} > T_{32} > T_{24} > T_{22} > T_{23} > T_{26} = T_{25}$. It was found that the risk coupling T value of the four factors is the highest. This indicates that, in the process of construction, operation and maintenance of the utility tunnel, although the probability of the four risk factors acting at the same time is small, the degree of its impact on the overall safety of the utility tunnel is the greatest. Additionally, the three-factor coupling risk T value is generally greater than the two-factor coupling risk T value, though there are also special cases, such as when the human-environmental two-factor coupling T value is greater than the human-equipment-management three-factor coupling T value. This also illustrates the complexity of the risk factor coupling relationship in the process of utility tunnel construction, operation and maintenance. In the two-factor coupling risk, the coupling value of human factors and environmental factors is the highest, indicating that there is a large coupling between human factors and environmental factors, which is the primary factor that should be considered in the risk management of utility tunnels. Thus, this paper selects the human-environmental two-factor coupled risk for further discussion and research.

4.2. Risk coupling path analysis and weight index calculation

The statistical analysis of the accident data related to utility tunnels from 2013 to 2022 using the NK model can conclude the highest degree of coupling between human factors and environmental factors in the construction, operation and maintenance of the utility tunnel, but the specific relationship between risk factors cannot be known, and thus, the path relationship between risk factors needs to be analyzed and determined for the next step of system dynamics modeling. In addition to the results of the LDA analysis, several researchers have also verified the scientific validity of the selected indicators [31–35].

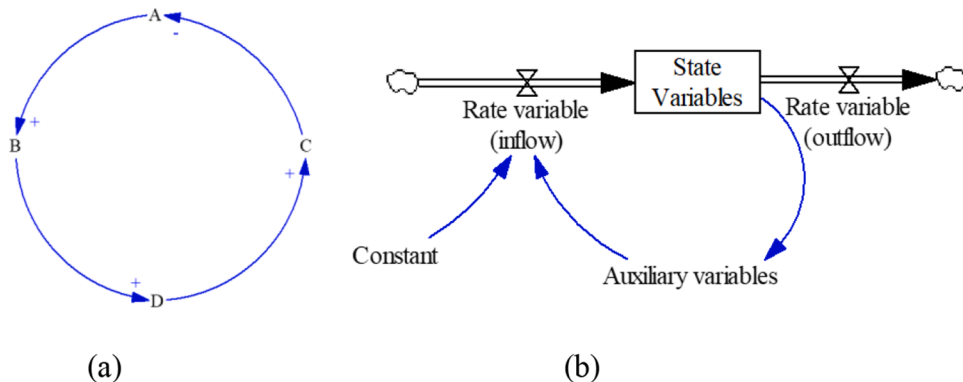


Fig. 5. Complete SD simulation model.

Table 2

Number and frequency of risk coupling in utility tunnel accidents.

Coupling form	Number and frequency of risk coupling				
Single-factor coupling	0000=0	1000=5	0100=2	0010=1	0001=1
	P ₀₀₀₀ =0	P ₁₀₀₀ =0.0667	P ₀₁₀₀ =0.0267	P ₀₀₁₀ =0.0133	P ₀₀₀₁ =0.0133
Two-factor coupling	1100=3	1010=4	1001=6	0110=2	0101=3
	P ₁₁₀₀ =0.04	P ₁₀₁₀ =0.0533	P ₁₀₀₁ =0.08	P ₀₁₁₀ =0.0267	P ₀₁₀₁ =0.04
Multifactor coupling	1110=8	1101=13	1011=13	0111=6	1111=5
	P ₁₁₁₀ =0.1067	P ₁₁₀₁ =0.1733	P ₁₀₁₁ =0.1733	P ₀₁₁₁ =0.08	P ₁₁₁₁ =0.0667

4.2.1. Interaction strength of hierarchical risk

In accordance with the method in Section 3.3.2, questionnaire interviews were conducted with experts, and Table 3 shows the judgment matrix between the levels of risk and the calculated maximum eigenvalues λ_{max} , the weight vectors, and the results of the consistency tests performed. In the table, it can be seen that all three judgment matrices pass the consistency test, so their normalized eigenvectors can be used as the weight vectors.

4.2.2. Interaction strength between Level II risks

After determining the path relationships and interaction strengths between Level I risk factors and the overall risk of the utility tunnel and those between Level II risk factors and their corresponding Level I risk factors, the next step is to identify the relevant pathway relationships and interaction strengths among the Level II risk factors. The method developed by Marle is applied to obtain the risk interaction strength of the bottom sub-risks. Fig. 6 shows the final obtained relevant paths and the interaction strength between Level II risks. For example, if the element (r_{22}, r_{13}) is equal to 0.263, then the probability of r_{22} originating from r_{13} is considered to be 26.3% under the condition that r_{13} is activated.

4.2.3. Determination of the initial value of the Level II risk factors

Ren uses the expert survey method and engineering experience to determine the scope risk of different risk levels [36]. His principle is used to divide the risk degree of each factor of the utility tunnel in this paper, and experts in the industry related to the utility tunnel are invited to score the selected Level II risk factors. However, when multiple experts conduct risk evaluations of the same risk factor, the evaluation results of multiple experts should be analyzed comprehensively because each expert has a different subjective awareness of the event, and a comprehensive result can be obtained by weighted averaging. The expert survey weight method is applied, meaning that the evaluation value of experts is corrected with weighting coefficients according to their seniority, titles and influence, and the initial value of secondary risk factors is determined. The experts are divided into 4 categories.

Table 3

Judgment matrix calculation results.

	Judgment Matrix	λ_{max}	Eigenvector	CI	CR	Pass the consistency test? (Y/N)
R	$\begin{pmatrix} R_1 & R_2 & R_3 & R_4 \\ R_1 & 1 & 2 & 3 & 2 \\ R_2 & 1/2 & 1 & 2 & 2 \\ R_3 & 1/3 & 1/2 & 1 & 1/2 \\ R_4 & 1/2 & 1/2 & 2 & 1 \end{pmatrix}$	4.071	(0.418 0.271 0.12 0.191)	0.024	0.027	Yes
R1	$\begin{pmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{11} & 1 & 1 & 3 & 2 \\ r_{12} & 1 & 1 & 3 & 3/2 \\ r_{13} & 1/3 & 1/3 & 1 & 1/3 \\ r_{14} & 1/2 & 2/3 & 3 & 1 \end{pmatrix}$	4.046	(0.352 0.324 0.099 0.226)	0.015	0.017	Yes
R2	$\begin{pmatrix} r_{21} & r_{22} & r_{23} & r_{24} & r_{25} \\ r_{21} & 1 & 1/2 & 1/2 & 1/7 & 1/2 \\ r_{22} & 2 & 1 & 1 & 1/5 & 2/3 \\ r_{23} & 2 & 1 & 1 & 1/3 & 5/8 \\ r_{24} & 7 & 5 & 3 & 1 & 7/3 \\ r_{25} & 2 & 3/2 & 8/5 & 7/3 & 1 \end{pmatrix}$	5.046	(0.072 0.123 0.135 0.484 0.186)	0.011	0.010	Yes

Table 4 shows the expert weight classification.

The initial values of risk factors for Level II are obtained by calculating the questionnaire results according to Eq. (8), and Table 5 shows the initial values of risk factors for Level II.

$$V_{ij} = \frac{\sum_{k=1}^n V_{ijk} \omega_k}{\sum_{k=1}^n \omega_k} \quad (8)$$

where $i=1,2$; $j=1,2,3,4$ for $i=1$; $j=1,2,\dots, 5$ for $i=2$. V_{ij} is the initial value of the risk factor for Level II, n is the number of experts and ω_k is the weight of the k^{th} expert. V_{ijk} is the scoring of the k^{th} expert on the ij^{th} risk.

4.3. System dynamics simulation modeling

There are many types of risks and complex coupling relationships during the construction, operation and maintenance of utility tunnels. If some unexpected uncertainties occur, the risk performance can be affected, which means excessive factor computing can hinder the model's analysis and practical meaning. Therefore, in this paper, based on the calculation results of the NK model, we select two Level I risk factors with the greatest degree of coupling and conduct a simulation study on the system dynamics of the coupling relationship between human-environmental coupling risks, to find the most obvious coupling relationship between the human risk and environmental risk, which can help reduce the occurrence of utility tunnel accidents and prevent the expansion of the impact after the accident.

4.3.1. Establishment of the SFD and the corresponding functional equation

Fig. 7 shows the SFD in the SD model. Since the SFD is generated based on the CLD and can describe the causal relationship between factors, the CLD diagram is omitted in this paper. The figure shows the relationship between the role of risk factors in the human-environmental coupling of utility tunnels. For example, when the risk factors r_{11} and r_{12} increase, the human risk increases, and the level of human-environmental coupling risk increases, while r_{13} and r_{14} have a negative effect on the human risk, which means that both the human risk and the human-environmental coupling risk levels decrease with increasing

	r_{11}	r_{12}	r_{13}	r_{14}	r_{21}	r_{22}	r_{23}	r_{24}	r_{25}
r_{11}	0	0.633	0	0.403	0	0	0	0	0
r_{12}	0	0	0	0.282	0	0.288	0	0	0.427
r_{13}	0	0	0	0	0	0	0	0	0.219
r_{14}	0	0.446	0	0	0	0	0	0	0
r_{21}	0	0	0	0	0	0	0	0	0
r_{22}	0	0	0.263	0	0.111	0	0	0.366	0
r_{23}	0	0	0.528	0	0	0	0	0	0
r_{24}	0	0	0	0	0.352	0	0	0	0
r_{25}	0	0	0.399	0	0.171	0.344	0.667	0	0

Fig. 6. The relevant paths and interaction strength between Level II risks.

Table 4

The expert weight classification.

Grade	Description of the Expert Level	Weight
1	Senior expert in the field of the utility tunnelSenior title of utility tunnel research, design and engineering personnel	1.0
2	Senior title of utility tunnel research, design and engineering personnelUtility tunnel managers with 11-20 years of service	0.9
3	Intermediate title of utility tunnel research, design and engineering staffUtility tunnel managers with 6-10 years of service	0.8
4	Junior title of utility tunnel research, design, engineering personnelWork experience of 1-5 years of utility tunnel managers	0.7

Table 5

Initial values of Level II risk factors.

Level I risk factors	Level II Risk Factors	Initial Value
Human- R_1	low staff safety awareness- r_{11}	39.28
	staff physical discomfort- r_{12}	15.09
	staff technical expertise- r_{13}	28.55
	staff psychological quality and emergency response capabilities- r_{14}	14.22
Environmental- R_2	natural disaster- r_{21}	48.62
	temperature, humidity and chemical gas concentration abnormalities- r_{22}	33.78
	third party construction impact- r_{23}	55.05
	illegal entry of people/animals- r_{24}	26.21
	staff working environment- r_{25}	32.16

r_{13} and r_{14} . In addition, except for the role of risks between hierarchical risks, there are also interactions between Level II risks. For instance, the working environment r_{25} is simultaneously exposed to natural disasters r_{21} , temperature, humidity and chemical gas concentration abnormalities r_{22} , third-party construction impact r_{23} and staff technical expertise r_{13} .

The eigenvectors calculated in Table 3 are used as weights for the horizontal variables, and the natural disasters exist as constants throughout the model system because they are not affected by other risk factors. Then, the INTEG function, the SMOOTH function and the DELAY3 function are used to construct a comprehensive system of functional equations for the coupled human-environmental risk SD model of the utility tunnel. In addition, the values in Fig. 7 are used as the coupling coefficients between the risk factors for level II, and Table 5 shows the initial values of the risk factors for level II. Table 6 shows the established functional equations.

4.3.2. Simulation

One year is used as the time for the SD model of the utility tunnel risk, the initial time is 0, the final time is 12, the time unit is one month, and the time step is 1.

The validity of the model should be checked before the simulation. If the model does not violate the basic common sense and rules, meaning that the rationality of the model itself has been checked, the validity and authenticity of the system are guaranteed. However, to be clear, the model cannot accurately reproduce "reality," and thus, to predict future changes, the model can only require the correctness of the trend of change. In the utility tunnel human-environmental coupling risk system, without input control factors, the value of the risk is bound to gradually increase. To demonstrate the simulation results after the model simulation has run successfully, Fig. 8 shows the change in the level of human-environmental coupling risk over time.

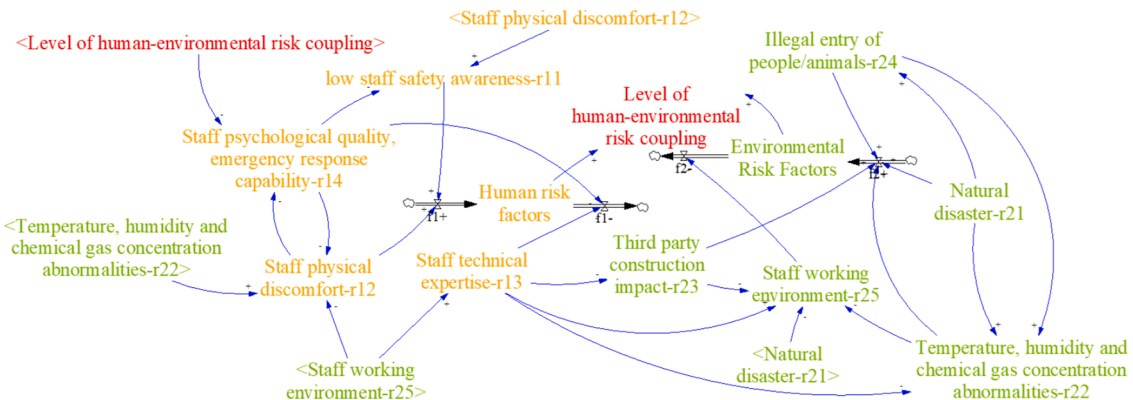


Fig. 7. SFD.

Table 6
Functional equations of the SD model.

Variable Type	Functional Equations
State Variables	$\text{Human risk factors} = \text{SMOOTH}(f_1 + "f_1-", 5)$ $\text{Environmental Risk Factors} = \text{SMOOTH}(f_2 + "f_2-", 5)$ $r_{11} = \text{INTEG}(-0.403 * r_{14} + 0.633 * r_{12}, 39.28)$ $r_{12} = \text{INTEG}(0.288 * r_{22} - r_{14} * 0.282 - 0.427 * r_{25}, 15.09)$ $r_{13} = \text{INTEG}(0.219 * r_{25}, 28.55)$ $r_{14} = \text{INTEG}(-(r_{12} * 0.446 + 0.418 / (0.418 + 0.271)) * 0.226 * \text{Level of human-environmental risk coupling}), 14.22)$ $r_{22} = \text{INTEG}(0.111 * r_{21} + 0.366 * r_{24} - r_{13} * 0.263, 33.78)$ $r_{23} = \text{INTEG}(-r_{13} * 0.528, 55.05)$ $r_{24} = \text{INTEG}(0.352 * r_{21}, 26.21)$ $r_{25} = \text{INTEG}(r_{13} * 0.399 - (r_{21} * 0.171 + r_{22} * 0.344 + r_{23} * 0.667), 32.16)$
Rate variables	$f_1+ = \text{SMOOTH}(\text{DELAY3}((0.352 * r_{11} + 0.324 * r_{12}) / 2, 3), 2)$ $f_1- = \text{SMOOTH}(\text{DELAY3}((0.099 * r_{13} + 0.226 * r_{14}) / 2, 3), 2)$ $f_2+ = \text{SMOOTH}(\text{DELAY3}((0.072 * r_{21} + 0.123 * r_{22} + 0.135 * r_{23} + 0.484 * r_{24}) / 4, 3), 4)$ $f_2- = \text{SMOOTH}(\text{DELAY3}(0.186 * r_{25}, 3), 1)$
Auxiliary Variables	$\text{Level of human-environmental risk coupling} = 0.418 / (0.418 + 0.271)$ $* \text{Human risk factors} + 0.271 / (0.418 + 0.271) * \text{Environmental Risk Factors}$
Constants	$r_{21} = 48.62$

From the simulation results, it can be seen that the change in the level of human-environmental coupling risk is consistent with the general rule and a further simulation analysis can be conducted. The rate of change of the risk level index gradually increases, indicating that the impact of utility tunnel accidents become increasingly serious with the simulation time, resulting in more serious consequential losses. Fig. 9 shows the change in the risk level of each factor over time; the simulation results show that, without putting in control factors, the risk brought by illegal invasion, temperature and humidity chemical gas in the corridor and external construction gradually increases and the working environment becomes harsh, which increases the risk of low safety awareness of the construction staff, while enhancing physiological discomfort, and gradually decreases the psychological quality emergency ability and degree of professionalism. In addition, since the natural disaster factor is not affected by other factors, its risk level maintains a straight line.

5. Results and discussion

5.1. Results

A coupling coefficient can be randomly selected to change its size, and the effect of the change in the coupling coefficient on the level of human-environmental risk coupling can be observed, which is the r_{23} - r_{25} coupling relationship in this paper. The coupling coefficient is changed by increasing by 10%, decreasing by 10% and decreasing by 20% to observe the changes in the human-environmental coupling risk level. Table 7 shows the variation in the coupling coefficient and Fig. 10 shows the variation in the human-environmental coupling risk level. The left image shows the variation in the complete simulation cycle. To clearly show the variation in the human-environmental coupling risk level, the image is enlarged and the enlarged image on the right depicts the lateness in the simulation period. Table 8 displays the values and the growth rates of the changes from August to December in the late simulation period.

From the simulation results, it can be seen that the third-party construction impact r_{23} and staff working environment r_{25} coupled risks gradually increase the level of human-environmental risk coupling. When the coupling coefficient increases, the level of human-environmental risk coupling increases, whereas when the coupling coefficient decreases, the level of human-environmental risk coupling decreases, and the growth rate decreases accordingly. Before the coupling coefficient is changed, the feedback situation between the coupling relationship should be analyzed and differentiated according to the influence situation between the factors. It can be seen from the SFD that although the r_{23} - r_{25} coupling relationship displays negative feedback, the influence of the staff working environment on the environmental risk is also a negative feedback relationship. Thus, for the r_{23} - r_{25} coupling relationship, reducing the coupling coefficient between the risk factors can effectively reduce the level and growth rate of the risk, which can increase the preparation time to prevent and control risks. Therefore, the impact of changes in the coupling coefficients of homogeneous and heterogeneous factors on the level of human-environmental risk coupling can be analyzed separately, and the risk factors and risk coupling relationships that have the most obvious impact on the level of human-environmental risk coupling can be identified, which can aid in the prevention of the overall construction, operation and maintenance risks of the utility tunnel.

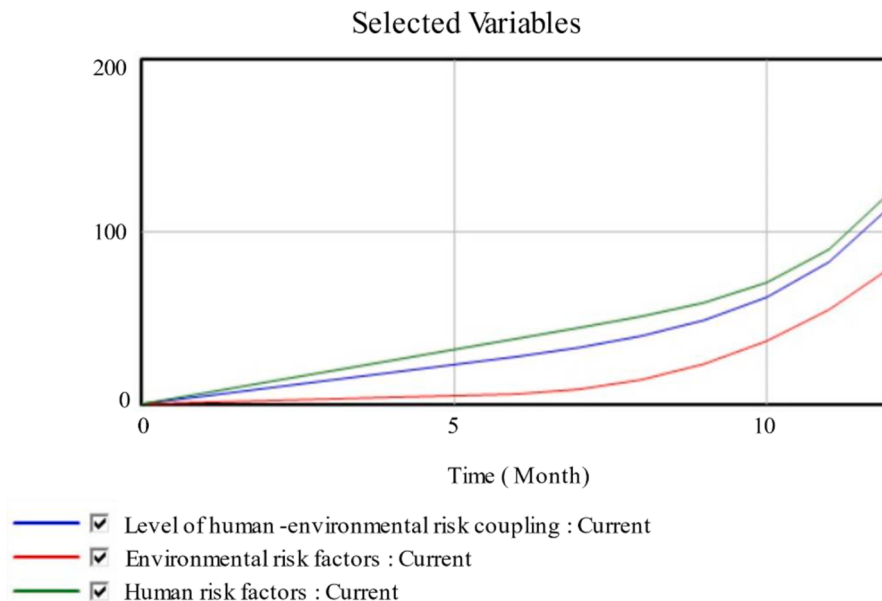


Fig. 8. Changes in the level of human-environmental coupling risk.

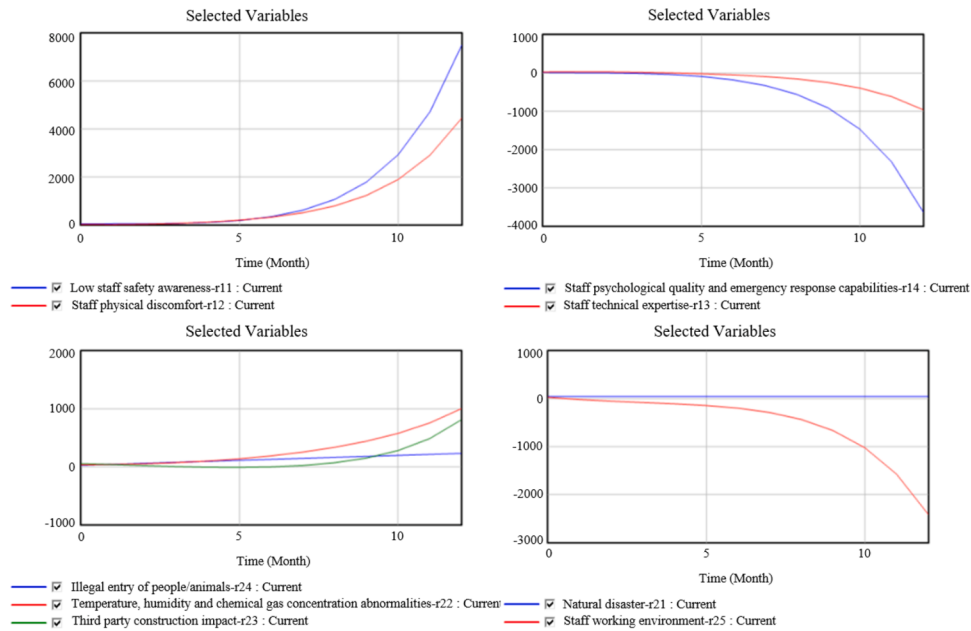


Fig. 9. Changes in the risk level of each factor.

Table 7

Variation in the coupling coefficient of r_{23} - r_{25} .

Program Name	Change ratio	Value after change
Current	0	0.667
Current 1	+10%	0.734
Current 2	-10%	0.600
Current 3	-20%	0.534

1 Changing the coupling coefficient of homogeneous factors

Homogeneous risk factors are risks that belong to the same category but have different causes, such as, for example, the coupling relationship between staff physical discomfort and low staff safety awareness in the Level I risk factor human risk. When risk accidents occur, homogeneous factors are often more likely to be coupled, and a 10% change in the coupling coefficient of homogeneous risk factors is applied to observe the change in the level of the human-environmental coupling risk. Table 9 shows the changes in the coupling coefficients after the analysis.

From (a) in Fig. 11, it can be seen that the adjustment of the corresponding coupling coefficients according to the feedback between the coupling relationships reduces the level of the human-environmental coupling risk. The impact of the r_{12} - r_{11} coupling relationship on the level of the human-environmental coupling risk is the most obvious

Table 8

Values and growth rates of changes from August to December.

Program/growth rate	8	9	10	11	12
Current	39.572	48.742	62.072	82.618	115.532
Growth rate		0.232	0.273	0.331	0.398
Current 1	39.797	49.311	63.273	84.948	119.841
Growth rate		0.239	0.283	0.343	0.411
Current 2	39.346	48.174	60.871	80.293	111.247
Growth rate		0.224	0.264	0.319	0.386
Current 3	39.123	47.614	59.690	78.010	107.050
Growth rate		0.217	0.254	0.307	0.372

Table 9

Changes in the coupling coefficients of homogeneous risk factors.

Program Name	Variation factor	Change ratio	Value after change
Current	/	0	/
H 1	r_{12} - r_{11}	-10%	0.570
H 2	r_{12} - r_{14}	-10%	0.401
H 3	r_{14} - r_{11}	+10%	0.443
H 4	r_{14} - r_{12}	+10%	0.310
E 1	r_{21} - r_{22}	-10%	0.100
E 2	r_{21} - r_{24}	-10%	0.317
E 3	r_{21} - r_{25}	-10%	0.154
E 4	r_{22} - r_{25}	-10%	0.310
E 5	r_{23} - r_{25}	-10%	0.600
E 6	r_{24} - r_{22}	-10%	0.329

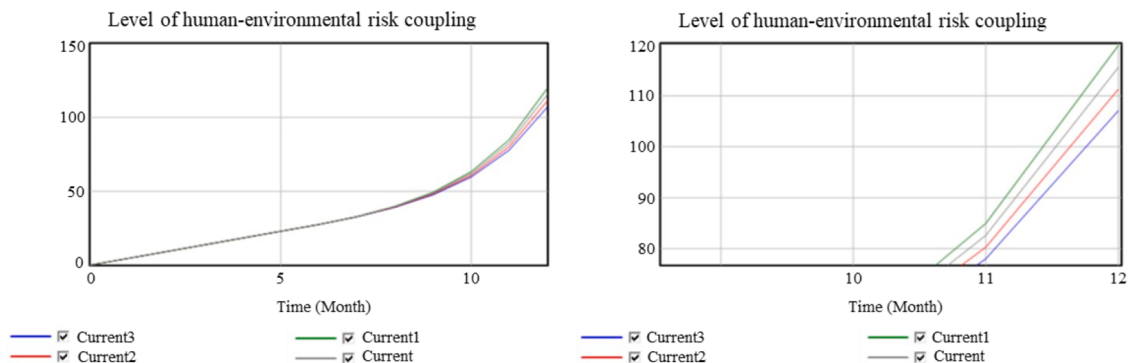


Fig. 10. Changes in the level of human-environmental coupling risks.

among human factors, followed by r_{12} - r_{14} , r_{14} - r_{12} , and r_{14} - r_{11} . To control the risk of utility tunneling, the first task related to human factors is to improve the physical condition of the staff, and then the aim can shift to focus on training staff to increase awareness of safety production and improve their psychological quality and emergency response capabilities.

From (b) in Fig. 11, it can be seen that the r_{23} - r_{25} coupling relationship among the environmental factors has the most substantial effect on the level of the human-environmental coupling risk, followed by r_{22} - r_{25} , r_{24} - r_{22} , r_{21} - r_{25} , r_{21} - r_{24} , and r_{21} - r_{22} . Therefore, to control the risk of a utility tunnel, the first task related to the environmental factors is to improve the working environment, and then attention can be paid to prevent the impact of third-party construction on the utility tunnel to monitor the concentration of temperature, humidity and chemical gases in the utility tunnel and to enact protective measures to prevent the illegal invasion of people and animals.

1 Changing the coupling coefficients of heterogeneous factors

Heterogeneous risk factors refer to the interaction of risks belonging to different categories, such as the staff working environment r_{25} and the staff physical discomfort r_{12} coupling relationship, which means the poor working environment will aggravate the already tired physical condition of employees, which in turn generates the corresponding accident risk. Table 10 shows the changes in the coupling coefficients after the analysis.

From (c) in Fig. 11, it can be seen that the r_{22} - r_{12} coupling relationship has the most substantial effect on the level of the human-environmental coupling risk, followed by r_{13} - r_{25} , r_{13} - r_{23} , r_{13} - r_{22} , r_{25} - r_{12} , and r_{25} - r_{13} . Therefore, to control the risk of the utility tunnel, the first task among the heterogeneous factors is to improve the physical condition of the staff to prevent reduction in the health of the staff due to internal environmental changes, and then it is necessary to improve the professionalism of the staff so that they can improve the working environment and better handle the impact of third-party construction.

By analyzing the coupling relationship between homogeneous and

Table 10

Changes in coupling coefficients of heterogeneous risk factors.

Program Name	Variation factor	Change ratio	Value after change
Current	/	0	/
HE 1	r_{13} - r_{22}	+10%	0.289
HE 2	r_{13} - r_{23}	+10%	0.581
HE 3	r_{13} - r_{25}	+10%	0.439
HE 4	r_{22} - r_{12}	-10%	0.259
HE 5	r_{25} - r_{12}	-10%	0.384
HE 6	r_{25} - r_{13}	+10%	0.241

heterogeneous factors, it was found that the level of human-environmental coupled risk gradually increases in the absence of input control factors, the most influential of which are r_{23} - r_{25} , that is, the impact of third-party construction on the working environment. Therefore, during the construction process, operation and maintenance of utility tunnels, we should focus on the impact of external construction, rational planning of the pipeline surrounding the environment, and minimizing the consequences of third-party construction. In addition, the improvement of the physical condition of the staff and the improvement of the level of professionalism should not be ignored. Improving the staff's ability to deal with unexpected accidents on the spot can effectively reduce the impact of utility tunnel accidents.

5.2. Discussion

5.2.1. Comparative analysis of coupling metric models

The models chosen for the study of risk coupling vary from field to field. In addition to the NK model, there are also interpretive structure models (ISM) [37], coupling degree models [38], and SHEL models [39]. However, the ISM cannot be used to compare and analyze the amount of coupling between factors, and two-factor coupling risk screening is needed in this paper, meaning that the ISM is not applicable. There is no uniform standard for the upper and lower limits of the covariates in the coupling degree model, and the index scoring relied on experts, which is subjective. The SHEL model requires realization and analysis around

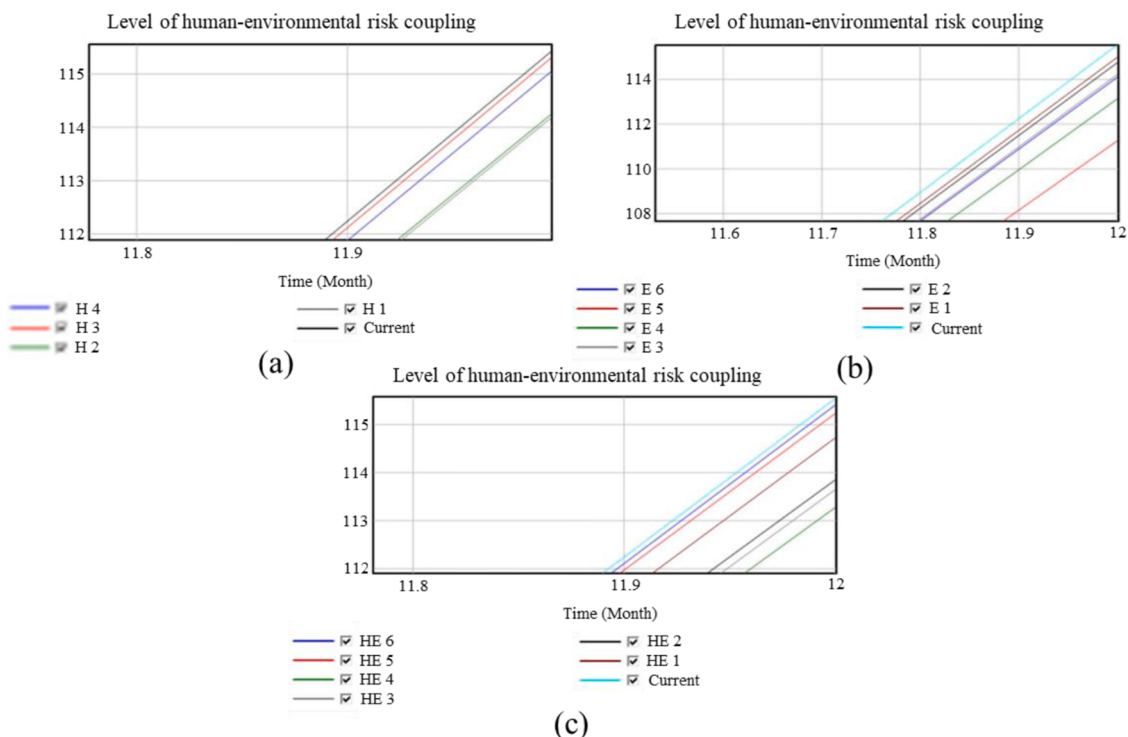


Fig. 11. Changes in the level of coupled human-environmental risk.

people, which is limited. The NK model can be used to evaluate the degree of coupling between the risk factors. Although a large amount of historical accident data is needed, the availability of utility tunnel accident cases in previous years is high. Therefore, this paper selects the NK model for the calculation of the coupling degree. In addition, risk assessment methods include Fault Tree Analysis (FTA) [40], Event Tree Analysis (ETA) [41], Bow-Tie (BT) [42], and Analytic Hierarchy Process (AHP) [43], but these static methods cannot provide an immediate update of risk probability, and the Bayesian Network (BN) [44] and Dynamic Bayesian Network (DBN) [45] in the dynamic methods also fail to describe the coupling path of risk and the impact of risk interaction on the dynamic risk. Therefore, SD is chosen in this paper to simulate the dynamic response process of risk coupling in utility tunnels.

5.2.2. Applicability of the model

The utility tunnel, as a complex system in engineering, usually has a long construction period, multi-technical intersection, vicious construction environment, crossing existing buildings or structures and other complex uncertainties. These uncertainties bring risks to the utility tunnel, resulting in collapse, explosion, mechanical injury and other accidents. There is a certain connection between a variety of risk factors. When two or more risks affect each other and are interactively coupled, the likelihood of an accident increases rapidly. Likewise, risk coupling exists for engineering projects with similar properties, such as subways, mines, and undersea tunnels [4,10,14], and the attention of researchers at this stage is mainly focused on the construction process and risk management for various accidents. Research on the coupling form, the coupling mechanism, the action law and the decoupling principle of risk coupling has been achieved in stages, and different methodological models can be applied to various fields to study the coupling mechanism and the degree of coupling. However, the degree and the type of risk that exists are different from the risk of utility tunnels due to different working environments, special processes, safety management measures, etc. The dynamic coupling risk assessment model proposed in this paper can be effectively applied not only to the field of utility tunnels but also to engineering projects with similar properties. Fig. 12 shows a theoretical framework we develop for similar risk coupling problems in engineering.

The specific steps are as follows.

Step 1. Data collection.

Web Spider technology is used to obtain relevant literature and accident reports in the field and a thorough analysis to gain some understanding of the research background, the current state of the research, and risk-related theory.

Step 2. Constructing the index system.

The LDA algorithm is used to analyze the collected text data, and the risk factors in the domain are identified and classified according to the analysis results. Note that all risk types should be included as much as possible to avoid omitting important risk factors due to oversight in the study.

Step 3. Risk coupling metrics.

By analyzing the nature and the applicability of the coupling metric model, the most suitable coupling metric model is found to analyze the coupling relationship between the risk factors. At the same time, the coupling coefficient between the risk factors can be calculated by combining the methods of determining the interaction strength of risks in the model.

Step 4. Simulation analysis.

The system dynamics simulation model is established to simulate the dynamic evolution path of risk coupling by establishing the causal relationship between factors and constructing the corresponding functional equations and then finding the path of risk coupling and the risk coupling relationship that has the main influence on the whole system.

Step 5. Risk control measures.

Risk control measures are proposed based on Steps 1-4, and risk control measures can be proposed in three stages: pre-coupling, during and post-coupling.

6. Conclusion

In this paper, a method of analyzing and simulating the risk coupling effect of utility tunnels based on the NK model and system dynamics is proposed, which is applied to actual cases of utility tunnels, and the specific conclusions are as follows.

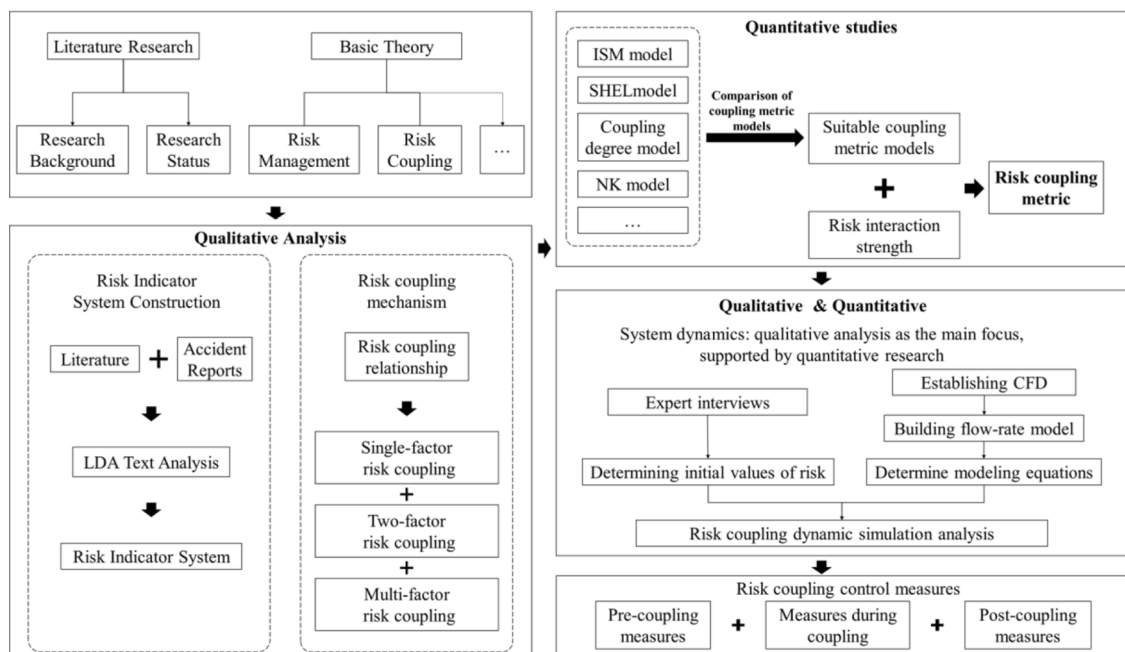


Fig. 12. A theoretical framework for similar risk coupling problems in engineering.

- (1) Using LDA to analyze the literature and incident reports of utility tunnels, the optimal number of topics is determined to be 4 through the perplexity curve, and four risk topics of human, equipment, environment and management are classified, as well as the risk indicators for each topic.
- (2) The coupling degree between risk factors is calculated using the NK model, and it was found that the four risk factors have the highest coupling T value. This indicates that, although the probability of the four risk factors having an effect at the same time is small, the degree of its impact on the overall safety of the utility tunnels is the greatest. In addition, the three-factor risk coupling T value is generally greater than the two-factor coupling risk T value, but there are special cases where the human-environmental two-factor coupling T value is greater than the human-equipment-management three-factor coupling T value. This is also an indication of the complexity of the risk factor coupling relationship in the process of utility tunnel construction, operation and maintenance.
- (3) Using the SD model for risk simulation of the utility tunnel example, the simulation results show that the law of change in the level of human-environmental risk coupling conforms to the universal law and effectively characterizes the change in the dynamic risk of the utility tunnel. By adjusting the interaction strength coefficients between risk factors for simulation, it was found that regulating the risk coupling relationship can effectively reduce the level and growth rate of the risk, and thus, increase the preparation time for the prevention and control of the risk. In addition, the degree of influence of all coupling relationships on the risk of a utility tunnel can be ranked to provide a theoretical basis for project decision-makers to assess the risks of the utility tunnel and enable project decision-makers to plan risk management actions more rationally.
- (4) In the case of the utility tunnel, the coupling relationship that has the greatest impact on the risk is the impact of third-party construction on the working environment of the staff, so the surrounding environment of the pipeline should be reasonably planned to minimize the consequences of third-party construction. At the same time, the improvement of the physical condition of the staff and the improvement of the professional level should not be neglected. Improving the staff's ability to deal with unexpected accidents on the spot can effectively reduce the impact of utility tunnel accidents.

In summary, the analysis and the simulation of risk coupling effects on utility tunnels can provide a decision basis for utility tunnel risk management, which enables decision-makers to more effectively assess the risks of utility tunnels and plan risk treatment actions. However, there are a few limitations that are worth discussing. First, the statistics of the utility tunnel accident data in this paper are not comprehensive enough, and the number of samples is small, which can be supplemented and improved in the future. Second, in the calculation of the risk interaction strength and the initial value of the bottom sub-risks, the expert interview method is applied, which has a theoretical basis but is subjective, and a more accurate method to determine the initial value of the system should be investigated in the future. Finally, due to the complexity of the coupling between the risk factors in utility tunnels, only the coupling relationship between human factors and environmental factors is selected for the simulation study in this paper, and the subsequent addition of management and equipment factors can be considered for multifactor coupling simulation to explore the changing trend of the overall risk level of utility tunnels under multiple risk factors.

CRedit authorship contribution statement

Nan Hai: Data curation, Writing – original draft, Conceptualization,

Methodology, Software. **Daqing Gong:** Supervision, Conceptualization, Investigation, Writing – review & editing, Methodology, Validation. **Shifeng Liu:** Writing – review & editing, Validation. **Zixuan Dai:** Visualization, Software, Data curation.

Declaration of Competing Interest

We confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication.

Data availability

Data will be made available on request.

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