

Using Bayesian network and Intuitionistic fuzzy Analytic Hierarchy Process to assess the risk of water inrush from fault in subsea tunnel

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Abstract. Water inrush from fault is one of the most severe hazards during tunnel excavation. However, the traditional evaluation methods are deficient in both quantitative evaluation and uncertainty handling. In this paper, a comprehensive methodology method combined intuitionistic fuzzy AHP with a Bayesian network for the risk assessment of water inrush from fault in the subsea tunnel was proposed. Through the intuitionistic fuzzy analytic hierarchy process to replace the traditional expert scoring method to determine the prior probability of the node in the Bayesian network. After the field data is normalized, it is classified according to the data range. Then, using obtained results into the Bayesian network, conduct a risk assessment with field data which have processed of water inrush disaster on the tunnel. Simultaneously, a sensitivity analysis technique was utilized to investigate each factor's contribution rate to determine the most critical factor affecting tunnel water inrush risk. Taking Qingdao Kiaocho Bay Tunnel as an example, by predictive analysis of fifteen fault zones, thirteen of them are consistent with the actual situation which shows that the IFAHP-Bayesian Network method is feasible and applicable. Through sensitivity analysis, it is shown that the Fissure development and Apparent resistivity are more critical comparing than other factor especially the Permeability coefficient and Fault dip. The method can provide planners and engineers with adequate decision-making support, which is vital to prevent and control tunnel water inrush.

Keywords: Bayesian network; IFAHP; risk assessment; subsea tunnel; water inrush

1. Introduction

In recent years, the subsea tunnel, which relies on a unique advantage, becomes the safest and most economical solution in the face of special environmental and geological conditions (Shekari 2021). Although the subsea tunnel makes a considerable contribution to Chinese engineering development, its security still faces more significant challenges than land tunnels. What is worse, the difficulty and low accuracy of underwater exploration, the corrosiveness of seawater to the structure, and the arching effect caused by high void water pressure, all increased the subsea tunnel's risk (Shen *et al.* 2008, Xue *et al.* 2021b).

Consequently, the water inrush disaster is the most severe challenge in constructing the subsea tunnel (Nilsen 2014). Especially in an unfavourable area such as fault fracture zones, high water pressure, large water volume, and strong sealing have caused the water inrush problem of subsea tunnels to be far more serious than land tunnels. For example, the Seikan Subsea Tunnel, which is the longest undersea tunnel in the world, experienced four major water inrushes during the construction process, causing the Seikan Tunnel construction to stall for 237 days and total construction period of the project reaches 21 years (Matsuo 1986, Xu 2009). Therefore, risk assessment plays a vital

role in avoiding the harm caused by tunnel water inrush during tunnel construction.

Risk assessment can identify and eliminate risk sources in engineering construction (Shi *et al.* 2017), and play a significant role in tunnel safety decision-making (Beard 2010). Generally, it is divided into qualitative analysis with quantitative analysis (Smith 1999). Xue *et al.* (2020) used the Delphi method and fuzzy set theory to calculate the optimal buried depth of immersed tunnels. (Peng *et al.* 2020) have established the AHP-cloud model for the water-rich fault tunnel that carried out water inrush risk assessment. (Ebrahimi *et al.* 2018) selected optimized concrete structure through AHP. (Li *et al.* 2015) described the risk of water inrush utilizing the method of combining weights quantitatively, which combined fuzzy mathematics and analytic hierarchy process. Additionally, machine learning is a useful tool for predicting water inrush risks (Xue *et al.* 2021a). (Wu and Zhou 2008) combined the geographic information system and the artificial neural network to predict groundwater inrush. (Cai *et al.* 2011) through the BP neural network algorithm to build a prediction model of subsea tunnel water inflow, which provides a new idea for predicting subsea tunnel water inflow. (Mahmoodzadeh *et al.* 2021) predicted the tunnel water inrush through six machine learning methods and compared the prediction results of each method to determine the best prediction model.

Although qualitative methods and quantitative analysis have made extraordinary contributions to engineering risk evaluation and analysis, they are limited to static control

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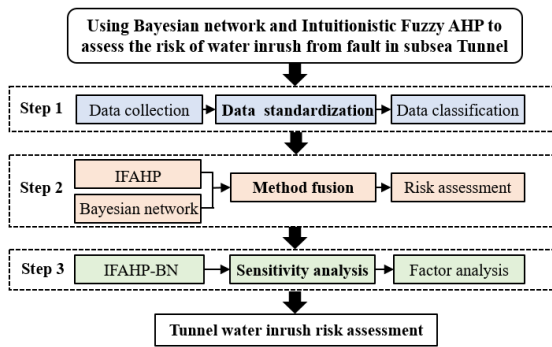


Fig.1 Main Structure of the paper

management and cannot be applied to the dynamic engineering environment which is constantly changing with the complex changes of the engineering environment (Zhang *et al.* 2016).

Bayesian network (BN) is a graphical model based on the probability relationship between variables. It combines prior knowledge and ideal data, which can be used to understand the problem domain, predict the results of intervention (Heckerman 1997). This method has significant advantages for the identification of water inrush in tunnels with complex and multi-risk factors. It can perform real-time dynamic diagnosis and analyze hazard factors (Jiang *et al.* 2014, Fattahi and Ilghani 2019), providing a useful decision analysis tool at any risk analysis stage. For instance, Sousa and Einstein (2011) combined the Bayesian network with tunnel data for geological correlation to build models and conducted a risk assessment for tunnel construction. (Hasanpour *et al.* 2010) evaluated the jamming risk of the TBMs in adverse ground conditions using Bayesian method. (Kouchami-Sardoo *et al.* 2019) assessed the risk of wind erosion based on BN, (Wang *et al.* 2020) established a rock damage classification prediction model using Bayesian method. Additionally, (Zhou *et al.* 2020) assessed the risk of the tunnel surrounding rock change points by Bayesian method, which improves the accuracy of tunnel collapse prediction.

Nevertheless, the traditional Bayesian network application for risk assessment is too subjective and depends on expert judgment. What is worse, it is not suitable for multi-factor complex situations, resulting in low accuracy and low credibility of the evaluation results. Therefore, it is necessary to propose a new comprehensive evaluation method for water inrush risk evaluation based on a Bayesian network.

In this work, the intuitionistic fuzzy analytic hierarchy process and Bayesian network were combined for water inrush risk assessment of tunnels crossing fault zones. According to the IFAHP, determine the prior probability of the Bayesian network. Meanwhile, combine tunnel field data, calculate the likelihood of water inrush disasters in real-time and use sensitivity analysis to determine the most critical factors affecting the water inrush risk. The main structure of article is shown in Fig. 1. This method uses IFAHP to replace the traditional expert experience method to obtain the prior probability. It overcomes the expert

method deficiencies of traditional Bayesian, avoiding existing models' shortcomings. Real-time prediction of tunnel water inrush risk is realised by classifying the processed field data and bringing it into the prediction model. Taking the Qingdao Kiaochow Bay Tunnel as an example, the prediction results are consistent with the actual engineering situation basically, which provides a new idea for the risk prediction of tunnel water inrush.

2. Risk analysis process of water inrush hazard in subsea tunnel

It is necessary to predict the probability of water inrush to ensure reliability to reduce water inrush hazards during construction. Here is a method based on IFAHP and BN to predict the risk of water inrush in a tunnel crossing a fault zone. The proposed method includes the following steps:

- (1) Determine the priority vector of hazard factors based on IFAHP.
- (2) Calculate the weight and bring it into the Bayesian network for the prior probability.
- (3) Combine the Bayesian network and processed data to predict risk level of tunnel water inrush.
- (4) Find the most critical factors affecting water inrush through sensitivity analysis.

2.1 Risk analysis method

2.1.1 Intuitionistic fuzzy analytic hierarchy process

Analytical Hierarchy Process (AHP) is a method that relies on the judgment of experts and makes pairwise comparisons to determine the priority scale through the scale of absolute determination (Saaty 2008). Nonetheless, AHP only relies on experts' subjective judgment and lacks objectivity, and it is exceptionally significant to introduce the concept of ambiguity in the decision-making process (Sadiq and Tesfamariam 2009). So in order to avoid subjectivity, (Ding *et al.* 2019) combined fuzzy theory with AHP to establish a risk assessment model of karst collapse, (Nikkhah *et al.* 2019) identified various risk groups using the TOPSIS and AHP multi-criteria decision-making methods. (Xue *et al.* 2019) determined the weight through combination of analytic hierarchy process and entropy method.

Intuitionistic fuzzy sets can show obvious superiority when dealing with fuzzy sets and uncertain fuzzy sets. What's more, the concept of hesitation could adjust the matrix that does not meet the consistency test. It is more suitable for pairwise comparison modelling widely applied in various fields (Xu and Liao 2013, Su 2020).

The specific steps of the intuitionistic fuzzy analytic hierarchy process (IFAHP) are as follows:

- (1) Establish an intuitionistic fuzzy judgment matrix

Establish a hierarchical structure according to the factors affecting water inrush, and build an intuitionistic fuzzy judgment matrix according to each layer $R_{ij}=(r_{ij})_{n \times n}$, $r_{ij}=(\mu_{ij}, \nu_{ij})$ is an intuitionistic fuzzy number, $\pi_{ij}=1-\mu_{ij}-\nu_{ij}$, μ_{ij} represents the degree of membership where the i factor is more critical than the j factor, and ν_{ij} represents the non-

membership where the i factor is more critical than the j factor.

(2) Judge matrix consistency test

Before performing the matrix consistency test, the original matrix $R_{ij}=(r_{ij})_{n \times n}$ tweak to $R'=(r'_{ij})_{n \times n}$.

The value r'_{ik} must meet the following requirements which shown in Eq. (1)

$$r'_{ik} = \begin{cases} (\mu'_{ik}, v'_{ik}), k > i + 1 \\ r'_{ik} = r_{ik}, k = i + 1 \\ (v'_{ik}, \mu'_{ik}), k < i + 1 \end{cases} \quad (1)$$

Among them

$$\mu'_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} \mu_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} \mu_{it} \mu_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1-\mu_{it})(1-\mu_{tk})}} \quad (2)$$

$$v'_{ik} = \frac{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} v_{it} v_{tk}}}{\sqrt[k-i-1]{\prod_{t=i+1}^{k-1} v_{it} v_{tk}} + \sqrt[k-i-1]{\prod_{t=i+1}^{k-1} (1-v_{it})(1-v_{tk})}} \quad (3)$$

The adjusted matrix is tested for consistency as Eq. (4):

$$d(R', R) = \frac{1}{2(n-1)(n-2)} \sum_{i=1}^n \sum_{k=1}^n (|\mu'_{ik} - \mu_{ik}| + |v'_{ik} - v_{ik}| + |\pi'_{ik} - \pi_{ik}|) \quad (4)$$

(3) Calculate the weight and priority vector

The weight:

$$\omega_i = \left(\frac{\sum_{k=1}^n \mu_{ik}}{\sum_{i=1}^n \sum_{k=1}^n (1-v_{ik})}, 1 - \frac{\sum_{k=1}^n (1-v_{ik})}{\sum_{i=1}^n \sum_{k=1}^n \mu_{ik}} \right), i = 1, 2, \dots, n \quad (5)$$

The priority vector :

$$\rho(W_i) = 0.5(1 + \pi_i)(1 - \mu_i) \quad (6)$$

Normalized priority vector:

$$W_i = \frac{\rho(W_i)}{\sum_i \rho(W_i)} \quad (7)$$

2.1.2 Bayesian network

The Bayesian network represents joint probability distribution (Friedman *et al.* 2000, Bidyuk *et al.* 2005), consisting of a Bayesian network structure and parameters. Besides, the Bayesian network structure is a directed acyclic graph constructed by several nodes representing variables and arrows connecting these nodes. The Bayesian network parameters describe the strength of the dependency relationship between nodes, and the connection is expressed with conditional probability. One-way and non-circular are the characteristics of Bayesian networks. Fig. 2 shows a primary Bayesian network. The Bayesian formula is the theoretical basis of the Bayesian network. When analyzing the probability of an event, quantitative analysis can be carried out based on actual problems and combined with

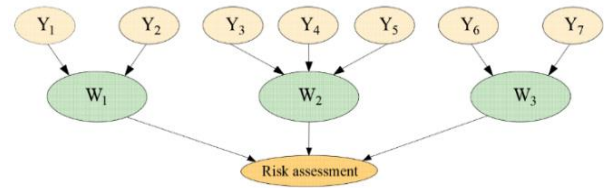


Fig. 2 Bayesian network

Table 1 Risk evaluation indicators

First indicators	Secondary indicators	Indicator type
Rock properties	Rock integrity Y ₁	Positive index
W ₁	Fissure development Y ₂	Negative index
Fault properties	Permeability coefficient Y ₃	Negative index
	Fault dip Y ₄	Positive index
W ₂	Apparent resistivity Y ₅	Negative index
Construction factors	Excavation disturbance Y ₆	Negative index
W ₃	Distance to sea level Y ₇	Positive index

probability theory basics to reduce the tedious reasoning process and complexity.

3. Risk assessment of tunnel water inrush based on IFAHP-BN

According to the current statistics of water inrush disasters, the largest water inrush among numerous hazard cases occurred in the Wulong tunnel that the water flux was measured up to 2.99×10^5 m³/h, while the smallest gushing water flux was reaching 5 m³/h in the Dasangyuan tunnel (Li *et al.* 2016, Xue *et al.* 2021c). Consequently, the water inrush risk is divided into three levels: High risk, Medium risk, and Low risk, which are based on the water flux range. When the water inflow is less than 1×10^2 m³/h, the risk of water inrush is low. The water inflow is between 1×10^2 m³/h and 1×10^3 m³/h, the risk grade of tunnel water inrush is medium. Besides, the water inflow is more than 1×10^3 m³/h, the probability of water inrush is high, which is considered as high risk. Three first-level indicators are selected: Rock properties W₁, Fault properties W₂, Construction factors W₃ and seven secondary indicators: Rock integrity coefficient Y₁, Fissure development Y₂, Permeability coefficient Y₃, Fault dip Y₄, Apparent resistivity Y₅, Excavation disturbance Y₆, Distance to sea level Y₇ (Li and Li 2014, Wang 2017).

(1) Establish an evaluation index system

From the three aspects of rock properties, fault properties, and construction factors, selected Rock integrity coefficient Y₁, Fissure development Y₂, Permeability coefficient Y₃, Fault dip Y₄, Apparent resistivity Y₅, Excavation disturbance Y₆, Distance to sea level Y₇, seven evaluation indicators, established a risk evaluation index system of subsea tunnel water inrush.

(2) Calculate the prior probability of the Bayesian network

Initially, establish an analytic hierarchy model, construct an intuitionistic fuzzy judgment matrix, and check the consistency. Through the intuitionistic fuzzy analytical

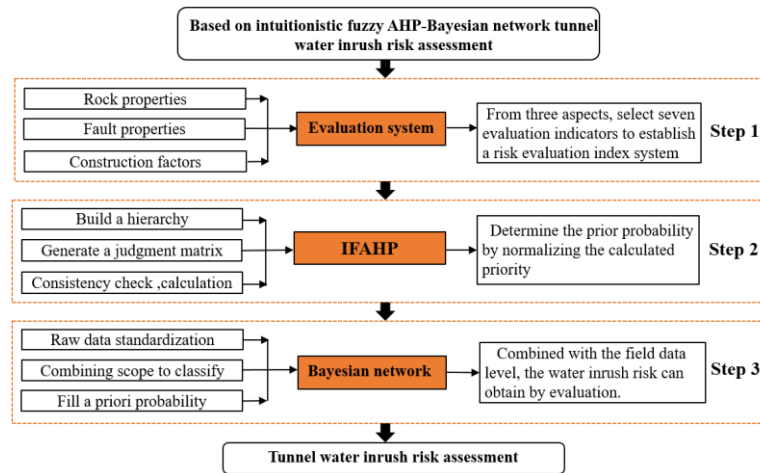


Fig. 3 Flow chart of risk assessment

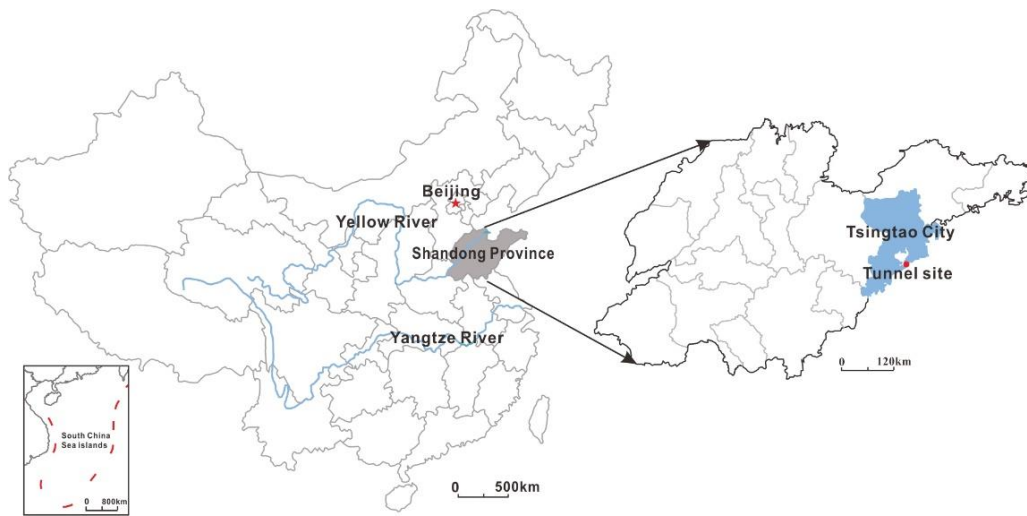


Fig. 4 The location of tunnel in this study

hierarchy process, calculate the prior probability of each node. Simultaneously, the data is standardized and according to the data range divided into three levels: High, Medium, and Low.

(3) Determine the level of water inrush risk

The prior probability obtained according to step (2) is substituted into the Bayesian network. Combined with the field data level, the risk level of the subsea tunnel crossing the fault zone can be obtained, and sensitivity analysis can be performed.

4. Study site

4.1 Background

Kiaochow Bay Subsea Tunnel, linking Tuandao with Xuejiadao, is located in Qingdao City of Shandong Province, China. The tunnel area is situated between the North China fault block's junction and the Yangtze fault block. The geological structure is the main body of the Cenozoic brittle fault structure. The region's internal fractures are mainly manifested as compression fractures

and shear fractures, which are mid-to new-generation brittle fracture structures with high angles ranging from several meters to tens of meters. The tunnel traverses six groups of 18 faults and has 22 types of lithology. The main tunnel's length is about 6,170 meters, the lithology is complex and changeable, and the risk of water gushing is high. The fault distribution is shown in Fig. 5.

This paper selects 15 fault zones for risk assessment of tunnel water inrush, the specific index data of 15 active fault zones are as follows in Table 2:

5. Risk assessment

5.1 Determine the prior probability of a node

5.1.1 Standardize indicators and rank

Positive index

$$x_{ij} = \frac{x_{j\max} - x_{ij}}{x_{j\max} - x_{i\min}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n; \quad (8)$$

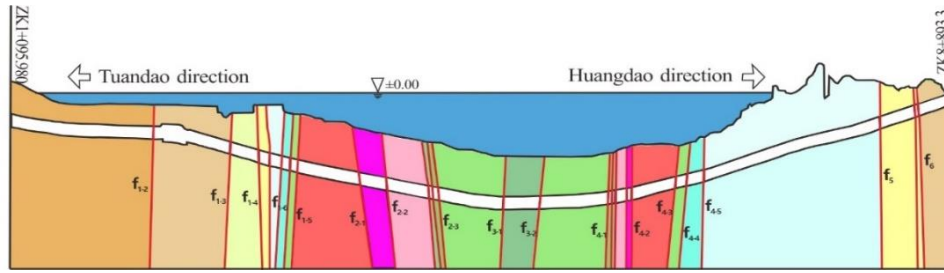


Fig.5 Fault distribution of Kiaocho Bay Subsea Tunnel

Table 2 Fault zone index value (Wang 2017)

Fault name	Rock integrity factor	Fissure development	Permeability coefficient	Fault dip	Apparent resistivity	Excavation disturbance	Distance to sea level
F1-1	1.8	0.56	0.015	88	390	0.6	13.5
F1-3	3.4	0.8	0.075	53	188	0.75	33.27
F1-4	2.2	0.76	0.04	85	343	0.98	40.24
F1-5	1.9	0.9	0.04	77	350	0.28	57.92
F1-6	2.1	0.85	0.075	83	296	0.72	44.31
F2-1	2.4	0.42	0.13	80	255	0.89	59.13
F2-2	2	0.38	0.045	73	320	0.63	62.16
F2-3	1.2	0.32	0.045	86	255	0.7	65.62
F3-1	0.8	0.52	0.015	55	338	0.4	68.46
F4-1	2.5	0.05	0.15	20	224	0.2	74.88
F4-2	3	0.01	0.075	23	265	0.5	68.92
F4-3	3.5	0.41	0.19	24	107	0.3	60.44
F4-4	2	0.35	0.045	51	298	0.62	57.08
F4-5	2.2	0.4	0.075	65	265	0.91	50.86
F5	1.9	0.82	0.03	70	302	0.45	24.38

Table 3 Standardized index value

Fault name	Rock integrity factor	Fissure development	Permeability coefficient	Fault dip	Apparent resistivity	Excavation disturbance	Distance to sea level
F1-1	0.6296	0.6180	0.0000	0.0000	1.0000	0.5128	1.0000
F1-3	0.0370	0.8876	0.3429	0.5147	0.2862	0.7051	0.6915
F1-4	0.4815	0.8427	0.1429	0.0441	0.8339	1.0000	0.5828
F1-5	0.5926	1.0000	0.1429	0.1618	0.8587	0.1026	0.3069
F1-6	0.5185	0.9438	0.3429	0.0735	0.6678	0.6667	0.5193
F2-1	0.4074	0.4607	0.6571	0.1176	0.5230	0.8846	0.2880
F2-2	0.5556	0.4157	0.1714	0.2206	0.7527	0.5513	0.2408
F2-3	0.8519	0.3483	0.1714	0.0294	0.5230	0.6410	0.1868
F3-1	1.0000	0.5730	0.0000	0.4853	0.8163	0.2564	0.1425
F4-1	0.3704	0.0449	0.7714	1.0000	0.4134	0.0000	0.0423
F4-2	0.1852	0.0000	0.3429	0.9559	0.5583	0.3846	0.1353
F4-3	0.0000	0.4494	1.0000	0.9412	0.0000	0.1282	0.2676
F4-4	0.5556	0.3820	0.1714	0.5441	0.6749	0.5385	0.3200
F4-5	0.4815	0.4382	0.3429	0.3382	0.5583	0.9103	0.4171
F5	0.5926	0.9101	0.0857	0.2647	0.6890	0.3205	0.8302

Negative index

$$x_{ij} = \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n; \quad (9)$$

The standardized value is shown in Table 3. According to the normalized value, the tunnel is divided into three levels: Low, Medium, and High. The values after classification are shown in Table 4.

5.1.2 Calculate the prior probability of a node

(1) Build a hierarchy

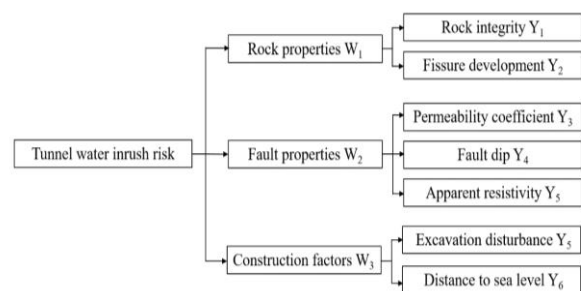


Fig. 6 Hierarchical structure model

Table 4 Index values of fault zone after classification

Fault name	Rock integrity factor	Fissure development	Permeability coefficient	Fault dip	Apparent resistivity	Excavation disturbance	Distance to sea level
F ₁₋₁	Medium	Medium	Low	Low	High	Medium	High
F ₁₋₃	Low	High	Medium	Medium	Low	High	High
F ₁₋₄	Medium	High	Low	Low	High	High	Medium
F ₁₋₅	Medium	High	Low	Low	High	Low	Low
F ₁₋₆	Medium	High	Medium	Low	High	Medium	Medium
F ₂₋₁	Medium	Medium	Medium	Low	Medium	High	Low
F ₂₋₂	Medium	Medium	Low	Low	High	Medium	Low
F ₂₋₃	High	Low	Low	Low	Medium	Medium	Low
F ₃₋₁	High	Medium	Low	Medium	High	Low	Low
F ₄₋₁	Medium	Low	High	High	Medium	Low	Low
F ₄₋₂	Low	Low	Medium	High	Medium	Medium	Low
F ₄₋₃	Low	Medium	High	High	Low	Low	Low
F ₄₋₄	Medium	Medium	Low	Medium	High	Medium	Low
F ₄₋₅	Medium	Medium	Medium	Medium	Medium	High	Medium
F ₅	Medium	High	Low	Low	High	Low	High

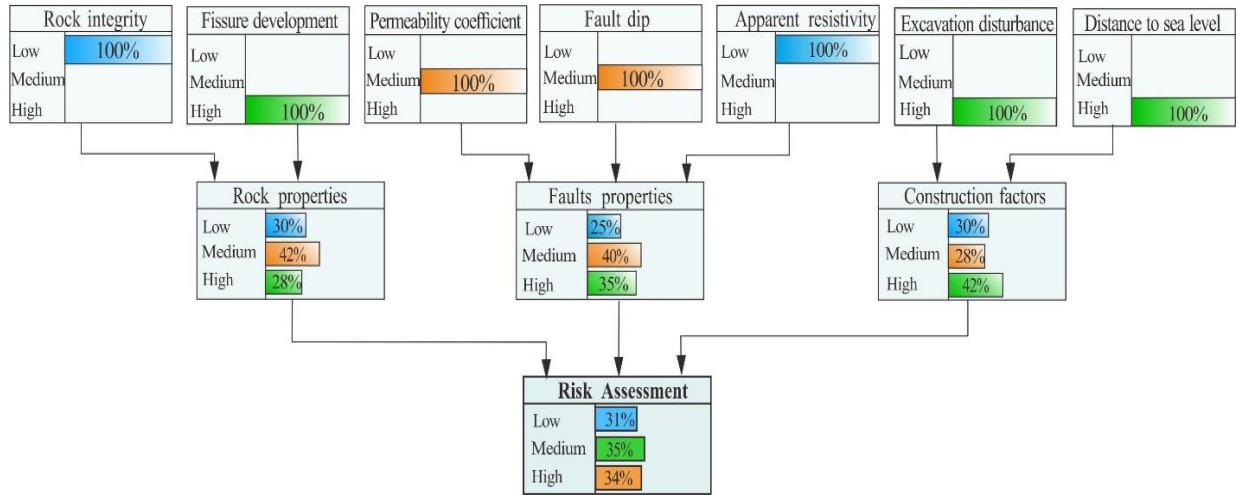


Fig.7 Bayesian network prediction

(2) Establish an intuitionistic fuzzy judgment matrix

$$R = \begin{bmatrix} \mu_{11}, v_{11} & \mu_{12}, v_{12} & \mu_{13}, v_{13} \\ \mu_{21}, v_{21} & \mu_{22}, v_{22} & \mu_{23}, v_{23} \\ \mu_{31}, v_{31} & \mu_{32}, v_{32} & \mu_{33}, v_{33} \end{bmatrix} = \begin{bmatrix} 0.5, 0.5 & 0.2254, 0.5094 & 0.45, 0.25 \\ 0.5094, 0.2254 & 0.5, 0.5 & 0.7396, 0.2604 \\ 0.25, 0.45 & 0.2604, 0.7396 & 0.5, 0.5 \end{bmatrix} \quad (10)$$

When $k > i + 1$, then $r'_{ik} = (\mu'_{ij}, v'_{ij})$

$$\mu'_{13} = \frac{\sqrt[k-i]{\prod_{h=i+1}^{k-1} \mu_{ih} \mu_{hk}}}{\sqrt[k-i]{\prod_{h=i+1}^{k-1} \mu_{ih} \mu_{hk}} + \sqrt[k-i]{\prod_{h=i+1}^{k-1} (1-\mu_{ih})(1-\mu_{hk})}} = \frac{\mu_{12} * \mu_{23}}{\mu_{12} * \mu_{23} + (1-\mu_{12}) * (1-\mu_{23})} \quad (11)$$

$$v'_{13} = \frac{\sqrt[k-i]{\prod_{h=i+1}^{k-1} v_{ih} v_{hk}}}{\sqrt[k-i]{\prod_{h=i+1}^{k-1} v_{ih} v_{hk}} + \sqrt[k-i]{\prod_{h=i+1}^{k-1} (1-v_{ih})(1-v_{hk})}} = \frac{v_{12} * v_{23}}{v_{12} * v_{23} + (1-v_{12}) * (1-v_{23})} \quad (12)$$

Judgment matrix consistency test

$$R = \begin{bmatrix} 0.5, 0.5 & 0.2254, 0.5094 & 0.4525, 0.2677 \\ 0.5094, 0.2254 & 0.5, 0.5 & 0.7396, 0.2604 \\ 0.2677, 0.4525 & 0.2604, 0.7396 & 0.5, 0.5 \end{bmatrix} \quad (13)$$

$$d(R', R) = \frac{1}{2(n-1)(n-2)} \sum_{i=1}^n \sum_{k=1}^n (|\mu'_{ik} - \mu_{ik}| + |v'_{ik} - v_{ik}| + |\pi'_{ik} - \pi_{ik}|) \quad (14)$$

$$= \frac{1}{2(3-1)(3-2)} (|\mu'_{13} - \mu_{13}| + |v'_{13} - v_{13}| + |\pi'_{13} - \pi_{13}|) < 0.1 (\text{Satisfy})$$

(3) Calculate the weight and priority vector

$$\mu_{ik} = \begin{bmatrix} 0.5 & 0.2254 & 0.4525 \\ 0.5094 & 0.5 & 0.7396 \\ 0.2677 & 0.2604 & 0.5 \end{bmatrix} \quad (15)$$

$$v_{ik} = \begin{bmatrix} 0.5 & 0.5094 & 0.2677 \\ 0.2254 & 0.5 & 0.2604 \\ 0.4525 & 0.7396 & 0.5 \end{bmatrix} \quad (16)$$

Weights

$$\omega_i = (\mu_i, v_i) = \left(\frac{\sum_{k=1}^n \mu_{ik}}{\sum_{i=1}^n \sum_{k=1}^n (1-v_{ik})}, 1 - \frac{\sum_{k=1}^n (1-v_{ik})}{\sum_{i=1}^n \sum_{k=1}^n \mu_{ik}} \right) \quad (17)$$

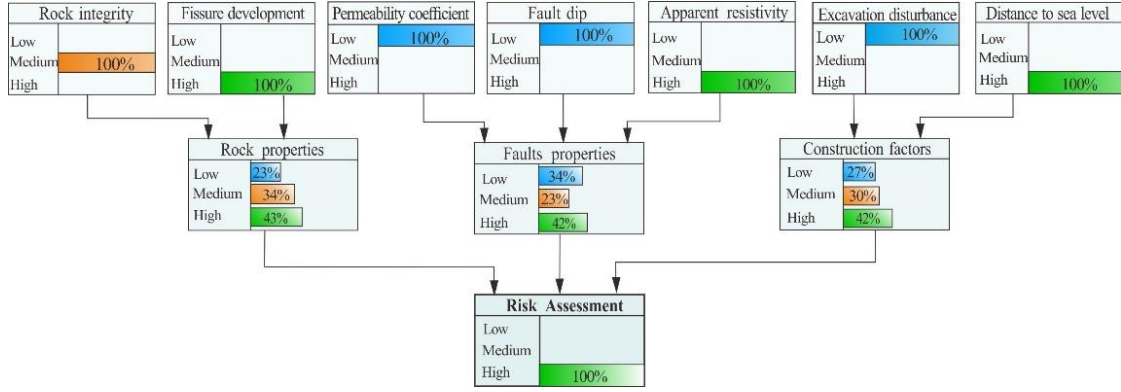


Fig.8 Sensitivity analysis

$$\mu_1 = \frac{\sum_{k=1}^n \mu_{ik}}{\sum_{i=1}^n \sum_{k=1}^n (1 - v_{ik})} = \frac{1.2698}{5.0523} = 0.2513 \quad (18)$$

$$v_1 = 1 - \frac{\sum_{k=1}^n (1 - v_{ik})}{\sum_{i=1}^n \sum_{k=1}^n \mu_{ik}} = 1 - \frac{1.8821}{3.9477} = 0.5384 \quad (19)$$

$$\mu_2 = \frac{\sum_{k=1}^n \mu_{ik}}{\sum_{i=1}^n \sum_{k=1}^n (1 - v_{ik})} = \frac{0.9858}{5.0523} = 0.1951 \quad (20)$$

$$v_2 = 1 - \frac{\sum_{k=1}^n (1 - v_{ik})}{\sum_{i=1}^n \sum_{k=1}^n \mu_{ik}} = 1 - \frac{1.2510}{3.9477} = 0.6831 \quad (21)$$

$$\mu_3 = \frac{\sum_{k=1}^n \mu_{ik}}{\sum_{i=1}^n \sum_{k=1}^n (1 - v_{ik})} = \frac{1.6921}{5.0523} = 0.3349 \quad (22)$$

$$v_3 = 1 - \frac{\sum_{k=1}^n (1 - v_{ik})}{\sum_{i=1}^n \sum_{k=1}^n \mu_{ik}} = 1 - \frac{1.9792}{3.9477} = 0.4986 \quad (23)$$

Priority vector

$$\rho(W_i) = 0.5(1 + \pi_i)(1 - \mu_i) \quad (24)$$

$$\rho(W_1) = 0.5(1 + \pi_1)(1 - \mu_1) = 0.5 \times (2 - 0.2513 - 0.5384) \times (1 - 0.2513) = 0.4530 \quad (25)$$

$$\rho(W_2) = 0.5(1 + \pi_2)(1 - \mu_2) = 0.5 \times (2 - 0.1951 - 0.6831) \times (1 - 0.1951) = 0.4514 \quad (26)$$

$$\rho(W_3) = 0.5(1 + \pi_3)(1 - \mu_3) = 0.5 \times (2 - 0.3349 - 0.4986) \times (1 - 0.4986) = 0.3879 \quad (27)$$

Normalized priority vector

$$W_i = \frac{\rho(W_i)}{\sum_i \rho(W_i)} \quad (28)$$

$$W_1 = \frac{\rho(W_1)}{\sum_i \rho(W_i)} = \frac{0.4530}{1.2924} = 0.35 \quad (29)$$

$$W_2 = \frac{\rho(W_2)}{\sum_i \rho(W_i)} = \frac{0.4514}{1.2924} = 0.35 \quad (30)$$

$$W_3 = \frac{\rho(W_3)}{\sum_i \rho(W_i)} = \frac{0.3879}{1.2924} = 0.3 \quad (31)$$

By analogy, calculate the probability value of all nodes.

5.2 Risk assessment of tunnel water inrush

Bring the prior probability calculated by IFAHP into the Bayesian network. By quantifying the actual field data, the classified data and the prior node probability calculated by IFAHP are brought into the Bayesian network. The evaluation result of the F_{1-3} is shown in Fig. 7. The hazard level of water gushing judged by the model is moderate.

The specific risk level evaluation of each fault is shown in the following Table 5.

From the Bayesian network analysis results of Table 5, it can be seen that the evaluation results of water inrush risk in this paper are basically consistent with the actual conditions of the project. Conversely, only the evaluation results of faults f_{2-1} and f_{4-1} are different from the project's existing conditions. The actual engineering risk level of faults f_{2-1} , f_{4-1} is medium risk. The medium-risk and high-risk probability of the risk evaluation in this paper are the same, and the evaluation results are relatively conservative.

5.3 Sensitivity analysis of tunnel water inrush factors

The Bayesian network can perform bidirectional reasoning when part of the state is known. Not only can the probability of water inrush risk in the tunnel be calculated according to the conditions of various influencing factors, but also the posterior probability of each corresponding node can be presented according to the failure conditions of the risk system to more vividly and intuitively identify the most likely combination of accidents.

The Bayesian network is constructed to diagnose the causes of water inrush accidents reversely. As shown in Fig. 8, after inputting relevant evidence, the entire Bayesian network system is updated. It can be seen that the three factors: Fissure development, Apparent resistivity, and

Table 5 Comparison of predicted with actual (Wang 2017)

Fault name	Prediction level	Actual level
F1-1	High	High
F1-3	Medium	Medium
F1-4	High	High
F1-5	High	High
F1-6	High	High
F2-1	Medium/High	Medium
F2-2	High	High
F2-3	High	High
F3-1	High	High
F4-1	Medium/ High	Medium
F4-2	Medium	Medium
F4-3	Medium	Medium
F4-4	High	High
F4-5	High	High
F5	High	High

Distance to sea level. They have a greater probability of causing water inrush. It shows that the most likely cause of the risk of water inrush in the large-section subsea tunnel crossing the weathering trough is the complex topography and geomorphology of the area where the subsea tunnel is located in deep seawater and high head pressure.

Due to the complicated engineering-geological conditions of the subsea tunnel and the particular fault structure, the selected evaluation index can only approximate the project's actual requirements. It cannot consider all the influencing factors. Consequently, it is reasonable that there is a specific deviation between the evaluation results and the actual working conditions.

6. Discussions

The risk analysis method proposed in this paper uses the combination of intuitionistic fuzzy analytic hierarchy process and Bayesian network. As discussed in the previous sections, which shows that the method proposed in this paper has specific feasibility and reliability. However, several issues should be addressed in future studies.

Firstly, in this study, due to the prior probability needs to satisfy the consistency test, the probability difference between high risk and low risk is 4% as shown in Fig.7. Therefore, it needs to make improvements to avoiding the probabilities of the three levels of the same node are relatively similar resulting in a small gap between the results.

In addition, considering the node's quantity, the index classification is relatively simple, and the index classification can be improved based on the actual situation, and the method structure can be optimized. At the same time, for different tunnel projects, the division of indicators can also be adjusted appropriately.

Then, because of the applicability of the proposed model in this study, it is highly recommended to apply in other types of tunnels in the future. For other types of tunnels such as mountain tunnels and subway tunnels, some indicator parameters need to be replaced according to the

actual situation of the project although there are some common parameters. Such as the mentioned in this article "Distance to sea level" can be replaced by "Groundwater level" in the water inrush risk assessment of mountain tunnels.

Consequently, it is still necessary to improve the accuracy and applicability of the evaluation results.

7. Conclusions

In this study, the assessment system that combining the evaluation index system and the prior probability is presented for predicting the level of water inrush of subsea tunnel. The water inrush risk was divided into three levels, the classification of the water inrush risk of subsea tunnels provides a reference for related research.

This paper proposed the method of IFAHP-BN into the risk assessment of water inrush in subsea tunnel. Taking Qingdao Kiaochow Bay Subsea Tunnel as an example, a total of 15 faults have been evaluated, and the prediction results of 13 fault zones are consistent with the actual situation, reflecting the feasibility of the method. The inspired model effectively improves the accuracy of the prediction results and provides a new method for predicting and determining the water inrush risk of fault activation in the subsea tunnel.

Additionally, seven factors influencing the water inrush of subsea tunnels and three water inrush grades were selected. The efficiencies of the seven influencing factors for water inrush of subsea tunnel were analyzed using the sensitivity analysis. The assessment result reflects that the Fissure development and Apparent resistivity are more critical comparing than other factor especially the Permeability coefficient and Fault dip. These results were conducive to guiding actual construction.

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