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# Risk assessment of tunnel water inrush based on Delphi method and machine learning

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The water inrush is one of the most catastrophic emergencies in metro tunnels. To avoid the potential water inrush, this paper proposes a risk assessment model for the metro tunnel based on Delphi survey method and machine learning. The proposed model consists of two parts, the risk assessment index system and the risk level prediction model. Firstly, by using the Delphi survey method, appropriate risk factors are assembled into the water inrush risk assessment index system. To guarantee the accuracy of prediction results, only the correctly selected risk factors, validated by Grey Relational Analysis (GRA), are recognized as assessment indexes. Then, the Radial Basis Function (RBF) network, improved by the Locally Linear Embedding (LLE) algorithm and the Particle Swarm Optimization (PSO), is applied to predict the risk level. Training and test sample sets are constructed using engineering data from Qingdao metro tunnel construction. In the comparison with baseline models, the proposed model demonstrates the best accuracy and mean square error, which are 92.5% and 0.015, respectively. The LLE-PSO-RBF model is applied to the Qingdao Metro Line 4 tunnel project. Three tunnels are predicted by invoking the trained model, and the risk level of water inrush is I, III and IV, respectively.

KEYWORDS

**water inrush, risk assessment, metro tunnel, Delphi method, RBF network**

## 1 Introduction

With increasing urbanization and growing transportation demands, metro tunnel engineering is developing rapidly. When tunneling, various disasters often occur caused by groundwater (Gong and Guo, 2021; Wang et al., 2020; Sousa and Einstein, 2021). The water inrush hazard is the most common issue encountered in tunneling engineering when interacting with groundwater, often resulting in serious loss of life and property (Zhu et al., 2022; Zhang et al., 2023c; Zhang et al., 2023a). Therefore, timely and effective assessment of the water inrush risk is of great significance in ensuring tunnel safety.

In tunnel engineering, water inrush disasters are influenced by various factors such as rock properties, hydrological conditions, and construction methods, making their underlying mechanisms extremely complex (Gong et al., 2025; Li et al., 2018; Xue et al., 2021; Gong et al., 2024; Feng et al., 2024; Wang et al., 2023; Wu et al., 2019). This complexity makes it difficult to measure the impact of different factors on water inrush disasters, which in turn complicates risk assessment. For comprehensive and objective selection of risk assessment indexes, the expert questionnaire survey method has been widely applied, combined with methods such as Delphi method (Kim et al., 2022), combined weighting method (Zhang et al., 2023b), and relative importance index (Shelake et al., 2022), etc., to reduce subjective influence. On the other hand, the collation and analysis of past disasters can help people recognize their mechanics and develop effective reference for prevention (Beard, 2010; Liu et al., 2022b; Liu et al., 2022a). Subsequently, scholars quantitatively assess risks with various methods, including Analytic Hierarchy Process (AHP) (Sun and Guan, 2024; Wu et al., 2011), cloud model (Yang et al., 2016), fuzzy comprehensive evaluation method (Li et al., 2011; Li and Zou, 2011), Fault Tree Analysis (FTA) (Hyun et al., 2015), risk matrix method, matter element expansion model, etc. Peng et al. (2020) proposed eight evaluation indexes and corresponding grading standards for water inrush by comprehensively analyzing the contributing factors, and established a cloud model for risk evaluation through the comprehensive standardization process and AHP with application to the Longjinxi Tunnel. Benekos and Diamantidis (2017) discussed three methods, qualitative, semi-quantitative and quantitative, and proposed a risk analysis and assessment methodology applicable to road tunnels based on the selection of the best integrated framework in terms of risk reduction, socio-economic factors, and safety measures. Ou et al. (2021) proposed a tunnel risk assessment model that integrates Dempster-Shafer (D-S) evidence theory and geological advance investigation, which was validated and applied in the Yuxi Tunnel. And with the development of Artificial Intelligence algorithms, it has become an indispensable tool for risk assessment in geotechnical engineering (Su et al., 2024; Liang et al., 2014; Gong, 2021; Lu et al., 2020; Zhang, 2024; Borg et al., 2014; Zhang et al., 2014; Zhang et al., 2016). Based on BN, Wang et al. (2014) proposed a tunnel risk probability assessment and predicted the damage risk of the existing property of the tunnel. Kovačević et al. (2021) developed a prediction model for long-term deformation of tunnels in soft rock strata based on Particle Swarm Optimization (PSO) and neural network. Feng and Zhang (2021) established a tunnel stability assessment model with adjacent tunnel construction as the main influencing factor based on neural network optimized by PSO. Mahmoodzadeh et al. (2021) systematically analyzed the applicability of six machine learning methods in predicting tunnel water inrush, including Long Short-Term Memory (LSTM), Deep Neural Networks (DNN), k-Nearest Neighbors (KNN), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Decision Trees (DT), and ranked their performance based on prediction accuracy.

In this paper, the case study of water inrush in different tunnel is used as a basis for analyzing and selecting the influencing factors using Delphi survey method. The risk assessment index system is constructed using the selected factors by referring to the Guidelines on Risk Assessment for Safety in the Design of Highway Bridge and Tunnel Engineering Works, whose accuracy is verified by GRA. Based on the RBF neural network improved with LLE algorithm and PSO, a risk prediction model of tunnel water inrush was established. The engineering data of Qingdao metro tunnel was collected as the learning dataset for the evaluation model, and the risk prediction results were compared with other methods. Finally, the model was verified by a real arithmetic example of Qingdao Line 4 between Jing-sha section.

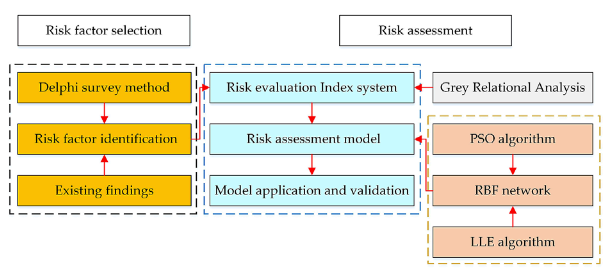


FIGURE 1
The flow chart of the proposed model.

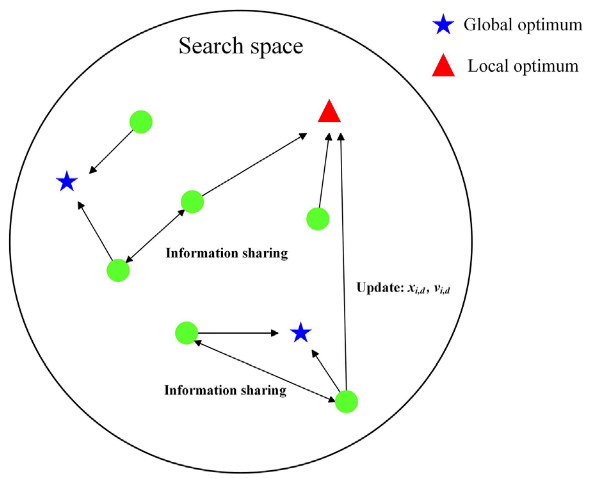


FIGURE 2
Conceptual diagram of the PSO.

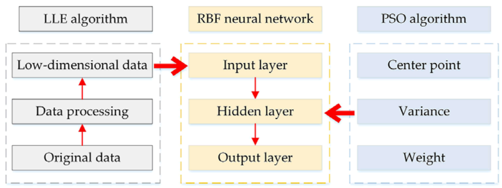


FIGURE 3
Schema of LLE-PSO-RBF network.

# 2 Evaluation methods and rationale

## 2.1 Overview of the assessment model

This paper proposed a novel risk assessment model for water inrush in metro tunnel, comprised a factor screening model to establish the risk assessment index system and a prediction model to predict the risk level. This model incorporates a variety of theories, including Delphi survey method, GRA, RBF network, LLE algorithm and PSO, which detailed process is shown in Figure 1.

The water inrush in metro tunnels is a result of the coupling interaction with various factors. As shown in Figure 1, based

TABLE 1 Analysis of main risk factors.

| Cases | Methods | Risk factors |
|---|---|---|
| A tunnel in Xinjiang, China | BP neural network | Engineering geology |
| | | Hydrogeology |
| | | Construction design |
| A tunnel in Henan, China | Comprehensive fuzzy evaluation | Other natural factors |
| | | Engineering geology |
| | | Hydrogeology |
| | | Construction design |
| | | Construction method |
| Yunshan Tunnel | AHP-ideal point method | Unfavorable geology |
| | | Stratum lithology |
| | | Hydraulic conditions |
| | | Human factors |
| A deep-buried extra-long tunnel | BP neural network | Unfavorable geology |
| | | Stratum lithology |
| | | Water table |
| | | Topography and landforms |
| | | Inclination of the rock layer |
| | | Fracture of surrounding rock |
| A tunnel in a fault zone | Set pair analysis model | Stratum lithology |
| | | Surrounding rock grade |
| | | Fault character |
| | | Fracture development degree |
| | | Surface water catchment area |
| | | Tunnel buried depth |
| | | Construction interference degree |

(Continued on the following page)

on investigating the existing findings, including water inrush assessment cases and relevant norms, the Delphi method is used to select potential water inrush evaluation indexes, which have a large impact. After several rounds of screening by the Delphi method, the water inrush assessment index system is established. Meanwhile, the GRA is introduced to verify the accuracy of the assessment index

TABLE 1 (*Continued*) Analysis of main risk factors.

| Cases | Methods | Risk factors |
|---|---|---|
| A karst tunnel | Combined empowerment TOPSIS method | Rock occurrence |
| | | Topography and landforms |
| | | Geological structure |
| | | Climatic precipitation |
| | | Stratum lithology |
| | | Water table |
| A tunnel in Kangding, China | Combined empowerment TOPSIS method | Disaster-pregnant environment |
| | | Disaster-causing factors |
| | | Positive driving factors |
| | | Negative driving factors |
| | | Disaster-bearing body |
| A tunnel in Yiwan, China | Multi-level fuzzy evaluation | Stratigraphic factors |
| | | Geological structure |
| | | Topography and landforms |
| | | Hydrogeology |

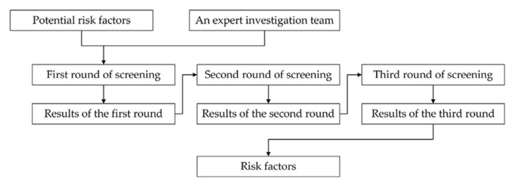


FIGURE 4
Delphi flow chart.

system. The subsequent prediction of the water inrush risk will not be proceeded unless the constructed assessment index system is verified for accuracy. Then, the RBF network is used as a tool for predicting the water inrush risk. In the RBF network architecture, the LLE algorithm is introduced for data preprocessing to eliminate redundant information, while the PSO algorithm is used to help the RBF network find the optimal parameter combination to improve computational performance. Finally, the constructed risk prediction model is validated and applied.

## 2.2 Delphi survey method

The Delphi survey method (Kim et al., 2022) is essentially a feedback anonymous inquiry method that provides multiple rounds of controlled feedback surveys and finally reaches the consensus

TABLE 2 Delphi investigation results.

| Main hierarchy | Subordinate hierarchy | First round | Second round | Third round | |
|---|---|---|---|---|---|
| | | (CVR) | (Importance) | (CVR) | (COV) |
| Engineering geology A | Grade of surrounding rock | 1.00 | 100 | 0.81 | 0.15 |
| | Rock mass integrity | 0.95 | 95 | 1.00 | 0.13 |
| | Weathering degree | 0.62 | 71 | 0.71 | 0.17 |
| | Fracture development | 0.62 | 90 | 0.62 | 0.17 |
| | Ratio of soft to hard strata | 0.43 | 65 | 0.43 | 0.27 |
| | Uniaxial compressive strength | 0.48 | 58 | – | – |
| Hydrogeology B | Permeability coefficient | 0.81 | 90 | 1.00 | 0.11 |
| | Catchment area | 1.00 | 88 | 1.00 | 0.12 |
| | Water head height | 0.62 | 91 | 0.71 | 0.2 |
| | Water-richness | 0.62 | 72 | 0.43 | 0.15 |
| Construction Design C | Buried depth of tunnel | 0.81 | 85 | 1.00 | 0.11 |
| | Tunnel section width | 0.62 | 85 | 0.71 | 0.17 |
| | Excavation disturbance | 0.38 | – | – | – |
| Natural condition D | Landform | 0.81 | 88 | 0.90 | 0.20 |
| | Average monthly rainfall | 0.90 | 84 | 0.81 | 0.16 |
| | Seasonal distribution | 0.14 | – | – | – |

of the expert group. This method, characterized by anonymity, feedback and statistics, can significantly eliminate the effect of authority and subjectivity on the results, making the evaluation results objective and credible, and avoiding the shortcomings that only reflect majority opinions in expert meetings. In this method, the importance of each survey result was determined by calculating the content validity ratio (CVR) of each round of survey results, which is shown in Equation 1.

$$\mathrm{CVR} = \frac{n_e - N/2}{N/2} \tag{1}$$

In Equation 1, $n_e$ indicates the number of members considering the element to be indispensable and $N$ is total number of team members. The closer the CVR is to 1, the more closely aligned the number of members considering the factor essential is to the total. The Coefficient of Variation (COV) is used to verify the final Delphi survey results, and if the COV is greater than 0.8, an additional round of investigation will be required for this result.

## 2.3 Grey relational analysis (GRA)

GRA is an analytical method that quantitatively describes the development trend of a system by assessing the correlation between reference and comparison data columns. It can demonstrate the magnitude of relation between different sequences, and can be used to characterize the sensitivity of results to different factors. The correlation coefficient is determined by five steps:

1. Determine the analysis sequence.

The risk level is defined as the parent sequence that reflects the characteristics of the system, and assessment indexes are defined as subsequences that affects the system. In this paper, the parent sequence and $n$ subsequences of the measured water inrush data of the $m$ (number of data groups) group are used to analyze and construct the original data matrix as shown in Equation 2.

$$[X] = \begin{bmatrix} x_{1,0} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,0} & \cdots & x_{m,n} \end{bmatrix} \tag{2}$$

2. Dimensionless processing.

Due to variations in dimensions across different indexes, the error is too large in the analysis and comparison, making it difficult to draw correct conclusions. In order to reduce the analysis error caused by different dimensions, the original data was processed

TABLE 3 Assessment indexes of tunnel water inrush.

| Level 1 index | Level 2 index | Risk level | | | |
|---|---|---|---|---|---|
| | | I (Low) | II (Mid) | III (High) | IV (Very) |
| Engineering geology A | Grade of surrounding rock A1 | I, II | III | IV | V, VI |
| | Rock mass integrity A2 | Intact | Relative | Crushed | Utterly |
| | Weathering degree A3 | (1, 0.9) | [0.9, 0.8) | [0.8, 0.6) | ≤ 0.6 |
| | Fracture development A4 | Not | Weak | Medium | Strong |
| | Ratio of soft to hard strata A5 | <25 | [25, 50) | [50, 75) | ≥75 |
| Hydrogeology B | Permeability coefficient B1 | <0.01 | [0.01, 1) | [1, 10) | ≥10 |
| | Catchment area B2 | <20 | [20, 40) | [40, 60) | ≥60 |
| | Water head height B3 | <10 | [10, 30) | [30, 60) | ≥ 60 |
| | Water-richness B4 | No | Slightly | Relative | Rich |
| Construction Design C | Buried depth of tunnel C1 | <10 | [10, 30) | [30, 50) | ≥50 |
| | Tunnel section width C2 | <8.5 | [8.5, 12) | [12, 14) | ≥14 |
| Natural condition D | Landform D1 | Flat | Ramp | Ravine | Denuded |
| | Average monthly rainfall D2 | <60 | [60, 80) | [80, 100) | ≥100 |

TABLE 4 Grey correlation between factors.

| | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| I | 0.96 | 0.94 | 0.49 | 0.97 | 0.89 | 0.66 | 0.89 | 0.88 | 0.67 | 0.91 | 0.70 | 0.66 | 0.69 |
| II | 0.93 | 0.79 | 0.74 | 0.76 | 0.94 | 0.54 | 0.94 | 0.79 | 0.54 | 1.00 | 0.89 | 0.86 | 0.91 |
| III | 0.93 | 0.89 | 0.76 | 0.88 | 0.94 | 0.82 | 0.94 | 0.86 | 0.61 | 0.91 | 0.93 | 0.86 | 0.91 |
| IV | 0.96 | 0.83 | 0.48 | 0.82 | 0.89 | 0.47 | 0.89 | 0.82 | 0.33 | 1.00 | 0.68 | 0.66 | 0.69 |
| | 0.95 | 0.86 | 0.62 | 0.86 | 0.91 | 0.62 | 0.91 | 0.84 | 0.54 | 0.95 | 0.80 | 0.76 | 0.80 |

using initial value method. The data processing is mathematically represented as shown in Equation 3:

$$X' = x_{ij}/x_{i1} \tag{3}$$

where $i = 1, 2, \cdots, \mathrm{m}; j = 0, 1, \cdots \mathrm{n}$.

3. Calculate the correlation coefficient.

The gray relational coefficient between the subsequence and the parent sequence is calculated according to Equation 4:

$$\xi_{ij} = \frac{\min\left\{|X'_{ij} - X'_{i0}|\right\} + \rho\max\left\{|X'_{ij} - X'_{i0}|\right\}}{|X'_{ij} - X'_{i0}| - \rho\max\left\{|X'_{ij} - X'_{i0}|\right\}} \tag{4}$$

where $\xi_{ij}$ is the correlation coefficient between the $i$th parameter of the $j$th subsequence and the $i$th parameter of the parent sequence, $\max\{|X'_{ij} - X'_{i0}|\}$ is the maximum difference between the parent sequence and subsequences, $\rho$ is the differentiation coefficient, with values in the range [0,1].

4. Correlation calculation.

The average value obtained by averaging the correlation coefficient series is the correlation degree, through Equation 5 as shown below:

$$\gamma_{0i} = \frac{1}{n}\sum_{i=1}^{n}\xi_{ij} \tag{5}$$

Correlation coefficient $\gamma_{0i} > 0.5$ indicates that there is a relatedness between the parent sequence and subsequences, and the $\gamma_{0i}$ closer it is to 1, the higher the correlation is between the two.

TABLE 5 Sample data.

| No. | Level | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | I | II | Intact | 0.85 | Not | 36.98 | 0.004 | 41.3 | 3.01 | Slightly | 12.6 | 6.2 | Flat | 59.5 |
| 2 | II | IV | Crushed | 0.5 | Weak | 84.4 | 2.851 | 69 | 8.84 | Rich | 12.8 | 6.2 | Flat | 59.5 |
| 3 | IV | V | Utterly | 0.3 | Medium | 85.7 | 4.493 | 77.2 | 12 | Rich | 14 | 6.2 | Flat | 59.5 |
| 4 | IV | VI | Utterly | 0.3 | Strong | 91 | 25.92 | 75 | 10.47 | Rich | 13.95 | 6.2 | Ramp | 59.5 |
| 5 | II | IV | Crushed | 0.7 | Weak | 34.48 | 0.001 | 11 | 1.28 | Slightly | 11.6 | 5.2 | Ramp | 57.9 |
| 6 | IV | V | Utterly | 0.3 | Strong | 69.56 | 5.184 | 28.4 | 3.27 | Relative | 11.5 | 5.2 | Ramp | 57.9 |
| 7 | II | V | Crushed | 0.5 | Strong | 21.8 | 0.004 | 0.1 | 0.1 | Slightly | 11 | 5.2 | Flat | 57.9 |
| 8 | II | V | Crushed | 0.5 | Weak | 53.84 | 5.184 | 31.2 | 3.25 | Slightly | 10.4 | 5.2 | Flat | 57.9 |
| 9 | IV | VI | Crushed | 0.2 | Medium | 94.12 | 15 | 77.4 | 9.73 | Rich | 13.6 | 6.4 | Ramp | 57.9 |
| 10 | III | V | Crushed | 0.4 | Weak | 93.75 | 0.1 | 74.5 | 11.92 | Rich | 16 | 6.4 | Flat | 57.9 |
| 11 | I | IV | Intact | 0.4 | Not | 32.65 | 0.01 | 1.63 | 0.16 | Slightly | 9.8 | 6.4 | Denuded | 57.9 |
| 12 | IV | VI | Utterly | 0.3 | Strong | 91.76 | 0.5 | 84.1 | 13.12 | Rich | 15.6 | 6.4 | Flat | 57.9 |
| 13 | II | II | Crushed | 0.8 | Medium | 52.9 | 0.5 | 21.0 | 22 | Relative | 25.5 | 9.0 | Ramp | 57.5 |
| 14 | I | II | Intact | 0.75 | Weak | 60 | 0.5 | 28.0 | 22 | Rich | 25 | 5.9 | Ramp | 57.5 |
| 15 | II | III | Crushed | 0.7 | Weak | 60 | 3.2 | 11.6 | 19 | Rich | 23 | 5.9 | Flat | 57.5 |
| 16 | III | II | Crushed | 0.85 | Medium | 111.5 | 0.5 | 75.1 | 18.6 | Relative | 20 | 5.9 | Flat | 57.5 |

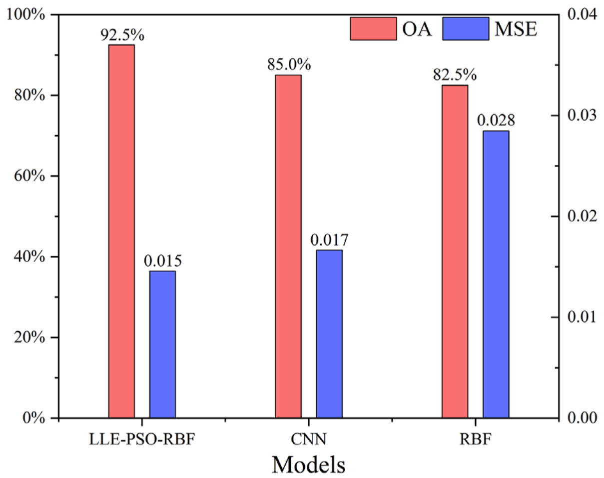


FIGURE 5
Results of the proposed model and baseline models.

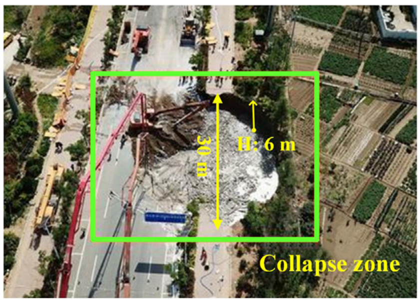


FIGURE 6
The ground collapse.

## 3 Improved RBF network model optimized with LLE and PSO

The RBF neural network, composed of input, hidden, and output layers, is a feed forward neural network renowned for its excellent classification and approximation capabilities (Wang et al., 2018). It has simple learning rule, fast convergence speed, high stability and strong self-learning ability, and can create more accurate estimation value under the condition of small number of samples (Liu et al., 2020).

In RBF network training, the more number and dimensionality of original data, the more time and amount of calculation are needed. Therefore, the LLE algorithm is used to reduce the data dimension, creating a low-dimensional data set to optimize the RBF input layer. The LLE algorithm is a non-linear dimensionality reduction method that maps data from a high-dimensional space

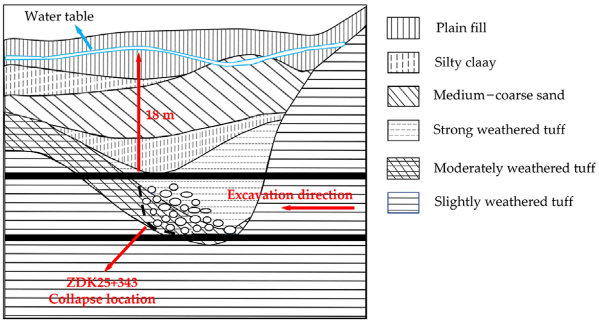


FIGURE 7
The geological conditions near the collapse area.

to a low-dimensional space while preserving the original structural information (Roweis and Saul, 2000). Its fundamental concept is to assume that the data is linear in a smaller local space, in which a certain point can be approximately linearly represented by other points in the neighborhood (Chen and Liu, 2011). It is calculated as follows:

1. Select point $X_i$ and its $k$ nearest neighbors $X_i^{(k)}$.

Suppose there are $D$ points in a space. Calculate the euclidean distance between point $X_i$ and the other $D-1$ points in the space, and select the $k$ points that are closest to point $X_i$.

2. Calculate the weighting coefficient $w_{ij}$ between $X_i$ and $X_i^{(k)}$.

$X_i$ can be approximated linearly from $X_i^{(k)}$ by a coefficient vector $w_i$. The $w_i$ is composed of a set $w_{ij}$, and satisfies the loss equation as shown in Equation 6.

$$w_i^* = arg_{w_i} min \frac{1}{2} ||X_i - w_i X_i^{(k)}||\ ^2 \tag{6}$$

where $arg_{w_i} min$ means finding the weights that minimize the loss function.

3. Construct low-dimensional data collections.

Assuming that the corresponding low-dimensional projections of $X_i$ and $X_i^{(k)}$ are $Y_i$ and $Y_i^{(k)}$, which satisfy the same linear relationship, the low-dimensional data is mathematically represented as shown in Equation 7:

$$Y^* = argmin_Y \sum ||Y_i - w_i^* Y_i^{(k)}||\ ^2 \tag{7}$$

where $Y^*$ is an $n \times d$ matrix that represents the low-dimensional embedding of the original data.

Additionally, as the RBF network uses the radial basis function as its activation function, the selection of center points significantly impacts its computational performance. Therefore, the PSO algorithm is introduced to help the RBF network find the optimal parameter combination. The PSO algorithm (Kennedy and Eberhart, 1995) is an method that can optimize nonlinear and multi-dimensional problems, the basic concept of which is to create a fully linked swarm in the space where particles move and share information amongst themselves to find the place that best suits their needs, as shown in Figure 2. Each particle has two attributes: position $x_{i,d}$ and velocity $v_{i,d}$, and it continuously updates its position according to Equation 8 and Equation 9,

$$x_{i,d}(it+1) = x_{i,d}(it) + v_{i,d}(it+1) \tag{8}$$

$$\begin{aligned} v_{i,d}(it+1) = \omega v_{i,d}(it) + C_1 \times Rnd(0,1) \times [pb_{i,d}(it) - x_{i,d}(it)] \\ + C_2 \times Rnd(0,1) \times [gb_d(it) - x_{i,d}(it)] \end{aligned} \tag{9}$$

where $\omega$ is the inertia weight, $C$ is constant, $Rnd$ is a random number ranging from 0 to 1, $pb_{i,d}$ is the optimal position of particle $i$, $gb_d$ is the optimal position of all particles.

The schema of improved assessment model is shown in Figure 3.

# 4 Model validation

## 4.1 Establishment of water inrush risk assessment index system

As water inrush hazards result from the coupling of various factors, the primary task in risk assessment is to identify the contributing factors. These factors are characterized as having a significant effect on the potential for tunnel water inrush. Therefore, the rationality of factor selection directly affects the reliability of subsequent risk assessment results.

Li et al. (2018) have conducted a detailed analysis of various water inrush disasters and their corresponding triggering factors by reviewing numerous tunnel water inrush cases. On this basis, while combining several risk assessment cases as shown in Table 1, the types of main factors influencing the tunnel water inrush have been identified. There are four types of factors, including engineering geology, hydrological conditions, construction design and other natural conditions.

The above-mentioned four types of factors are first-level indexes affecting water inrush, which need to be further refined into second-level indexes before conducting the risk level prediction. In order to ensure the objective and accurate selection of possible risk factors, Delphi multi-round survey method was used for screening. In this study, an expert investigation team with 30 invited experts was formed, including professors of tunnel engineering, design experts and researchers with advanced experience. After that, the above-mentioned potential risk factors were screened to identify secondary risk indexes, based on an anonymous feedback method involving two rounds of screening and one round of validation, as shown in Figure 4.

The risk factors listed in Table 1 are specific to a particular project and are not directly applicable to a new project. To establish a universal risk assessment index system, we derived the risk factors in Table 2 based on previous research findings, combined with our experience in tunnel engineering and expert consultations. And then, a questionnaire was designed to survey these factors.

In the first round of Delphi survey, experts evaluated the rationality of the 16 risk factors in the inquiry form and calculated the CVR value to verify the applicability of these factors. After calculation, two factors were considered unsuitable for subsequent assessment, as a CVR value of less than 0.4. The remaining 14 factors proceeded to the second round of screening, where the expert investigation team scored each factor according to its importance. In

TABLE 6 Data from different tunnels.

| No. | A1 | A2 | A3 | A4 | A5 | B1 | B2 | B3 | B4 | C1 | C2 | D1 | D2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | II | Intact | 0.8 | Not | 16.2 | 0.0026 | 21.6 | 1.4 | Relative | 16.2 | 7.4 | Flat | 118.6 |
| 2 | IV | Crushed | 0.75 | Medium | 87.4 | 0.5184 | 77.2 | 15.94 | Rich | 17.7 | 7.4 | Flat | 118.6 |
| 3 | V | Crushed | 0.7 | Strong | 80 | 0.5184 | 74.2 | 17.9 | Rich | 19 | 7.4 | Denuded | 118.6 |

the second round, one factor was unsatisfactory for risk assessment with a score of less than 60 and therefore it was not considered for participation in the third round of Delphi survey. The remaining 13 elements are selected as the contents of the third round of inquiry form, and the results of the first two rounds of inquiry form and the survey data of Qingdao tunnel are attached for experts' reference to judge the feasibility of each factor as risk evaluation index. Meanwhile, the COV was used to verify the final investigation result. If the COV is greater than 0.8, an extra round of investigation needs to be added for the result. The results show that all 13 risk elements CVR and COV meet the requirements, which indicates that they can be used as the secondary index for constructing the risk assessment system.

In accordance with the results of the three rounds of survey, the tunnel risk evalua-tion system was established finally, including 4 primary index layers and 13 secondary dependent indexes. With the risk factors selected, they are categorized into different ranges corresponding to different risk levels. Based on engineering specifications, while considering the geological characteristics and construction features of Qingdao area, the risk assessment index system for water inrush in metro tunnel is proposed as shown in Table 3.

In addition, GRA was used to verify the reasonableness of risk factor selection. Taking the risk level as the parent sequence and the quantitative index values as the subsequence, the gray correlation coefficients between the parameters were calculated and homogenized, and the correlations obtained are shown in Table 4. In Table 4, the correlation of all factors was greater than 0.5, indicating that the risk factors selected based on the Delphi survey method were reliable and reasonable.

## 4.2 Model analysis

In this paper, 16 groups of tunnel data of Qingdao Metro were selected as the training data for the assessment method. The source of this dataset is the geological and construction materials of the different section tunnels in Qingdao Metro, including, Kai-sheng section of Line 1, Shui-kai section of Line 1, Shi-miao section of Line 2, Wu-nan section of Line 2 and Xin-zhao section of Line 6, thus it is very reliable and trustworthy. In training, the 13 quantified risk factor indexes were used as input data for the input layer, and the water inrush risk class was output from the output layer. During training, the order of the dataset was disrupted, and the data was divided into a training set and a test set in a 70:30 ratio. The sample data of each tunnel section is shown in Table 5.

To validate the effectiveness of the proposed model, the RBF neural network and CNN were used as baseline models. Meanwhile, to mitigate the effect of randomness, the test was repeated 10 times, using overall accuracy (OA) and mean squared error (MSE) as evaluation metrics. The detailed comparison results are shown in Figure 5. It can be seen that the proposed model achieves the best OA and MSE, with values of 92.5% and 0.015, respectively, among the three models. This indicates that the proposed model has the best predictive performance. In contrast, the OA of the CNN and RBF models are relatively lower, at 85% and 82.5%, respectively, while their MSE are larger, at 0.017 and 0.028, respectively. The possible reasons for the weak prediction of the baseline models are twofold. Firstly, the hyperparameters of the RBF and CNN models need to be manually tuned. Additionally, the training data is relatively small, and the feature distribution is imbalanced. By constructing the LLE-PSO-RBF model, the prediction performance is improved with small samples.

# 5 Case study

## 5.1 Project overview

The Jing-sha section of Qingdao Metro Line 4 is located between Jingang Road Station and Shazikou Station, Laoshan District, Qingdao. On 27 May 2019, while tunneling to ZDK25 + 343, a catastrophic water inrush occurred. The tunnel water inrush ultimately led to a large-scale ground collapse, forming a deep pit approximately 6 m in depth and 30 m in diameter, as shown in Figure 6. Figure 7 shows the geological conditions near the collapse region, where the strata consist of plain fill, silty clay, a medium-coarse sand layer, and tuff. The rock classification of the tunnel surrounding is Grade V, characterized by a broken rock mass and well-developed fractures. And under the impact of blasting construction, the rock mass is further damaged, increasing the risk of disasters. The tunnel is buried at a depth of approximately 19.6m, with the water table relative to the tunnel vault at 19 m. The thickness of the saturated sand layer is 7.1m, and it is prone to erosion by water flow due to its loose properties. The overburden of the tunnel vault is strongly weathered rock, with a thickness of only 0.7 m. In this unfavorable situation, continuous rainfall exacerbates the conditions.

## 5.2 Risk prediction with the proposed model

In this section, the trained LLE-PSO-RBF model is invoked to predict the water inrush risk for the metro tunnel. Data from three tunnel sections are collected for model prediction, as shown in Table 6, with No. 3 representing the data from the aforementioned water inrush disaster tunnel.

Based on the model predictions, the water inrush risk levels for the three tunnels are I, III, and IV, respectively. During the actual construction, the management failed to properly recognize the significant potential risks. In response to the water seepage at the site, the construction staff used conventional treatment methods. However, the actual water inflow during the inrush incident was 4,755.8 $m^3$, demonstrating that this disaster exceeded the empirical judgment (4,154.4 $m^3$). This highlights the importance of conducting risk level assessments in advance, as it enables staff to implement early safety measures and effectively prevent the occurrence of disasters. Based on the evaluation results, on-site construction measures can be adjusted and improved to establish a dynamic mechanism for construction management.

# 6 Conclusion

In this paper, a novel risk assessment model for water inrush in metro tunnels is proposed, including factor selection and risk prediction. The performance of the proposed model is verified by comparison with baseline models, and it is applied to assess a real project. The main conclusions are as follows:

1. The main risk factors causing tunnel water inrush disaster are identified as engineering geology, hydrological conditions, construction design, and natural conditions, based on which the risk assessment index system for water inrush of metro tunnel is established with 13 risk factor indicators. The correlation between risk indexes and risk levels is calculated using the GRA, indicating that the selection of risk factors is reasonable as the correlation of each factor is greater than 0.5.
2. Constructed a water inrush risk level prediction model for metro tunnels based on the improved RBF model, which is optimized by LLE algorithm and PSO algorithm. Different model prediction results comparison proves that the proposed model have better risk assessment performance. The model is invoked to predict the water inrush risk level of the Jing-sha section in Qingdao Metro Line 4, and the predicted results of each tunnel is I, III and IV.

Tunnel water inrush is the result of the multi-factor coupling effect. The complex correlation between risk factors has influence on assessment results, but in this paper, its influence is not considered. Therefore, selecting risk factors which are independent and unaffected by other factors is an issue that should be considered for subsequent water inrush risk assessments. In addition, applying different methodologies is necessary to reduce the subjectivity effect in factor selection.

# Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

# Author contributions

LD: Conceptualization, Investigation, Supervision, Writing–original draft. QW: Conceptualization, Funding acquisition, Investigation, Methodology, Writing–original draft. WZ: Data curation, Software, Writing–original draft, Writing–review and editing. YZ: Data curation, Validation, Writing–original draft, Writing–review and editing. XL: Formal Analysis, Methodology, Writing–review and editing. FL: Formal Analysis, Investigation, Software, Validation, Writing–review and editing.

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# Conflict of interest

Author QW was employed by China Railway 20th Bureau Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

# Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

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