The risk assessment and prediction of water inflow into tunnels of Guangzhou Metro Line 21

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Abstract. In order to decrease the negative influence of water inflow on tunnel construction, the risk of water inflow should be evaluated and predicted. Based on the method of experts’ evaluation, combined with practical project, an assessment system of water inflow into mountain tunnel was set up, in which 9 evaluation indicators were proposed from the geological factors, hydrologic conditions and engineering three aspects, and every index weight was counted with the method of AHP. With BP neural network as an assessment tool, an integrated prediction model for water inflow into mountain tunnel was established. The assessment and prediction results for water inflow into tunnel of Guangzhou Metro line 21 were compared with results of expert classification. It shows that the error of BP neural network forecasting structure by means of AHP is not more than 3%, and it matches the required precision.

1. Introduction
Water inflow into tunnel not only brings hidden dangers to tunnel construction safety, but also has negative impacts on subsequent operations and causes unnecessary economic losses. Water inflow has already become a major geological hazard in the construction of tunnels and underground engineering. Therefore, it is significant to evaluate and predict the risk of water inflow.

Based on the weighted average method, Zhu established a risk assessment model for water inrush with the use of a multi-factor single comprehensive indicator evaluation method [2]. Li took a fuzzy comprehensive evaluation model to assess the risk of water inrush and landslide in the ultra-shallow section of an underwater tunnel [3]. Based on the Analytic Hierarchy Process (AHP), a comprehensive evaluation of the Wulingshan No.2 karst tunnel was conducted using a two-level fuzzy comprehensive evaluation method by Luo [4]. Ma focused on the uncertainty and multi-sources of the main control factors in the evaluation process, and managed to apply the fuzzy variable evaluation model to the assessment of flooding disasters in karst tunnels [5]. Xu and Shen studied the influencing factors and control weights of tunnel inrush water based on analytic hierarchy process, put forward a risk assessment method for water inrush and mud in tunnels [6, 7]. The above results are subject to the subjectivity of the evaluators and the randomness of the evaluation process during the evaluation process. Therefore, it is difficult to obtain objective and accurate evaluation results.

As the problem of water inflow into tunnel is influenced by many factors, its evaluation and prediction is nonlinear and highly complex. The neural network is a nonlinear dynamic system. Therefore, it is considered that the neural network combined with the analytic hierarchy process can be
applied to risk evaluation and prediction. AHP method is used to determine the weights of various indexes, and BP neural network is aimed to construct a risk assessment model for water inflow into tunnels to improve the accuracy of evaluation.

2. Comprehensive risk assessment method

2.1. Hierarchy analysis structure.
A risk assessment model for water inflow disaster in tunnel was established and the evaluation indicators included geological conditions, water conditions and engineering practices. These indicators constituted the criteria layer. According to the actual situation of the project, the standard layer is established to evaluate the water inflow risk, as shown in Figure 1.

![Figure 1. Evaluation indicators of water inflow disaster risk in mountain tunnel](image)

2.2. Analytic hierarchy process.
Analytic hierarchy process (AHP) splits the overall goal into sub-objectives. Under the structure matrix, the weight of each layer element is defined by the construction matrix. Finally, the final weight of each solution to the total goal is determined, so that the total ranking table is obtained.

Considering the importance of each element of a certain layer to a certain level of the previous layer, the judgment matrix of each element is constructed in turn.

Take \( a_{ij} \) as the result of importance comparison between the \( i^{th} \) element in a layer to the \( j^{th} \) sub-goal on the previous layer, so

\[
 a_{ij} = \frac{1}{a_{ji}}. \tag{1}
\]

The judgment matrix:

\[
 A = (a_{ij})_{n \times n} = \begin{bmatrix}
 a_{11} & a_{12} & \cdots & a_{1n} \\
 a_{21} & a_{22} & \cdots & a_{2n} \\
 \vdots & \vdots & \ddots & \vdots \\
 a_{n1} & \cdots & \cdots & a_{nn}
\end{bmatrix}. \tag{2}
\]

The eigenvalues and eigenvectors are calculated for each judgment matrix to find the eigenvector corresponding to the largest eigenvalue. The eigenvector is the weight vector calculated by the sum method and the steps are as follow:
(1) Normalize the columns of elements in the judgment matrix

\[ \bar{a}_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad (i, j = 1, 2, \ldots, n). \]  

(3)

(2) Find the sum of each element in each row

\[ \bar{W}_i = \sum_{j=1}^{n} \bar{a}_{ij} \quad (i, j = 1, 2, \ldots, n). \]

(4)

(3) Normalize

\[ W_i = \frac{\bar{W}_i}{\sum_{j=1}^{n} \bar{W}_j} \quad (i, j = 1, 2, \ldots, n). \]

(5)

The \( W_i \) is the weight vector.

The consistency of the important grades of each element obtained from the judgment matrix can be calculated by the following steps:

(1) Calculate \( \lambda_{\text{max}} \).

\[ \lambda_{\text{max}} = \frac{1}{n} \sum_{i=1}^{n} (A \cdot W) \]

(6)

(2) Calculate consistency indicators CI

\[ CI = \frac{\lambda_{\text{max}} - n}{n - 1}. \]

(7)

(3) Calculate the random consistency ratio CR

\[ CR = \frac{CI}{RI}. \]

(8)

In formula (8), RI is the random consistency indicator whose value is shown in Table 1, and CR is the random consistency ratio. When CR \( \leq 0.10 \), the constructed judgment matrix passes the consistency test, otherwise, the judgment matrix needs to be reconstructed. The total ranking of the levels is the weighting of all factors of a certain level on the total goal from the highest level to the lowest level.

| Order n | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  |
|---------|----|----|----|----|----|----|----|----|----|
| RI      | 0  | 0  | 0.58 | 0.90 | 1.12 | 1.24 | 1.45 | 1.32 | 1.41 |

### 2.3. BP neural network

The BP neural network trains the network mainly through the forward propagation of the signal and the backward propagation of the error. Its learning rule is to constantly correct the weight and threshold of the training network through error propagation so that the error can reach the required accuracy [8].

The higher the complexity of the neural network structure, the stronger its ability to deal with nonlinear problems, and the longer it takes to train the network. If the neural network structure is too simple, it is difficult to achieve convergence when training the network. Robert proved that any closed-interval continuous function can be approximated by a BP neural network with a hidden layer [9]. Therefore, a neural network with a hidden layer can be used to predict the inrush risk level.
2.4. Evaluation index pretreatment.
The pretreatment of evaluation indicators is mainly to make the types of evaluation indicators consistent and convert the evaluation indicators into dimensionless indicators [10]. The evaluation indicators are divided into the following three types according to the index attributes: extremely small, very large, and middle indicators.

(1) Converting the evaluation indicators into the same type, and $X$ is the processed evaluation indicator. For the processing of very small or very large evaluation indicators

$$X = M - x, x > 0.$$  

(9)

For the treatment of centered evaluation indicators:

$$X = \begin{cases} 
2(x - m), m \leq x \leq \frac{M + m}{2} \\
2(M - x), \frac{M + m}{2} < x \leq M
\end{cases}. $$  

(10)

In the formula: $m$ is the minimum value that the evaluation index can take; $M$ is the maximum value that the evaluation index can take.

(2) Turning the evaluation index into a dimensionless index can eliminate the influence of dimension, $\min X$, $\max X$, and $\mid X$, which are evaluation indexes, respectively extremely small, extremely large, and centered evaluations after normalization.

2.5. BP neural network algorithm.
The essence of the BP algorithm is to calculate the minimum value of the error function, and to modify the weights and thresholds according to the back propagation of the error function [11].

Error back propagation modify weight coefficient can be calculated as follow:

$$\Delta W_{ij} = -\eta \frac{\partial e}{\partial W_{ij}}.$$  

(11)

In the formula: $\eta$ is the learning rate; $e$ is the error function; $W_{ij}$ is the weight coefficient.

The usual weight modification formula:

$$w_{ij}(t + 1) = w_{ij}(t) + \Delta w_{ij} + a(w_{ij}(t) - w_{ij}(t - 1)).$$  

(12)

In the formula: $a$ is the potential factor.

2.6. AHP-based BP neural network evaluation process.
The comprehensive risk assessment process is roughly divided into: using the analytic hierarchy process (AHP) to build the evaluation model to determine the reasonable weight of each evaluation index, training the BP neural network, and applying the test sample to predict and evaluate.

$$I = \sum_{j=1}^{n} w_{j}x_{j}.$$  

(13)

In the formula: $w_{j}$ is the jth indicator weight, and $x_{j}$ is the jth indicator value.

According to the calculation results, the security levels are classified and the comprehensive risk assessment levels are shown in Table 2.

| Risk level | A | B | C | D | E |
|------------|---|---|---|---|---|
| Score      | 0.80-1.00 | 0.65-0.80 | 0.50-0.65 | 0.25-0.50 | 0-0.25 |

A: Very safe, B: Safe, C: Safe, D: More dangerous, E: Very dangerous.
3. Engineering application

3.1. Engineering survey.
Guangzhou metro line 21 is one of the routes in Guangzhou metro construction, which is about 61.6 kilometers. The research object in this paper is the 12 section of guangzhou metro line 21, which contains two shallow buried tunnels, all of which are constructed by mining method. According to the field survey, the research area is located in the suburb of guangzhou, with roads, houses, factories, construction sites and farmland, nurseries and orchards, including important traffic routes such as guangzhou-shantou highway. The soil layer mainly consists of silty clay and sandy clay, whose thickness is generally 8~15 m. The underlying bedrock is mainly granite, and the weathering is unevenly distributed.

The construction of tunnel has caused a change in the groundwater environment, creating a large additional load of the surrounding rock and supporting structure and the formation of the surrounding rock is unstable. In addition, the groundwater seepage during the construction of tunnel can lead to the tunnel flooding and water breaking, which seriously affects the construction schedule and safety of the tunnel. At the same time, the construction of the tunnel will also have a great influence on the construction area and the surrounding environment, including the lowering of underground water level and the change of underground water quality. Therefore, it is very important to evaluate and forecast the risk of tunnel surge in the construction process, and it is also the premise to ensure the safety of tunnel construction.

3.2. Risk assessment of water gushing in tunnel.
According to the evaluation index system of the water inflow into tunnel, five senior experts are consulted to construct the judgment matrix. According to formula (2) ~ (4), the eigenvalue and weight vector are obtained. In order to reduce the subjective influence of the evaluation staff, the weighted vector is calculated on average weight, and the final weight vector $W$ is obtained.

$$R_w = \begin{bmatrix} B_1 & B_2 & B_3 \\ 0.545 & 0.311 & 0.144 \end{bmatrix}$$ (14)

The weight of each stratified index can be obtained, as shown in Table 3. According to the weight of each index obtained in Table 3, it can be seen that in the 9 factors that affect the water inflow into tunnel, the strength of the surrounding rock, the fracture zone of the overlying bedrock to the roof, the development of the surrounding rock fracture, the water rich water, the overlying water pressure, and the depth of the tunnel embedment have a significant impact on the water risk of the tunnel. Therefore, the BP neural network model is established by using these six indicators as input layer to predict the risk of water inflow into tunnel.

| X  | A   | Index weight |
|----|-----|--------------|
|    |     | B1 (0.545) | B2 (0.311) | B3 (0.144) |
| X1 | 0.309 |             |             |             | 0.168 |
| X2 | 0.198 |             |             |             | 0.108 |
| X3 | 0.493 |             |             |             | 0.269 |
| X4 | 3     | 0.403       |             |             | 0.125 |
| X5 |       | 0.597       |             |             | 0.186 |
| X6 |       |             | 0.139       |             | 0.020 |
| X7 |       |             |             | 0.019       | 0.003 |
Table 4. Classification of rock fracture condition

| Crack situation                                                                 | Score |
|-----------------------------------------------------------------------------|-------|
| The fissure surface is very rough, the width is zero, and the rock is hard and discontinuous. | 0–2   |
| The fissure surface is slightly rougher, the width <1mm, and the fissure surface rock is hard. | 2–4   |
| The fissure surface is slightly rougher, the width <11mm, the fissure surface rock is weak. | 4–7   |
| Crack face smooth or thickness <5mm weak interlayer, crack width 1-5mm, continuous. | 7–9   |
| Thickness >5mm soft interlayer, crack width >5mm, continuous. | 9–10  |

According to the geological survey data of the 12 section of guangzhou metro line 21, the quantitative indicators (the strength of the surrounding rock, the distance from the upper strata to the roof, the water rich water, the overlying water pressure, and the buried depth) are directly obtained from the survey data, and the qualitative indicators (the development of the tunnel surrounding rock fractures) are obtained according to the classification criteria. The classification of fracture condition is shown in Table 4, and the tunnel survey is shown in Table 5. The most significant influence on tunnel water inflow in the six indicators, X1, X2, and X8 are very large index. According to the formula (9), extremely large indexes are transformed into very small indexes, removing indicators dimension, the comprehensive risk assessment are calculated as shown in Table 6.

The most important evaluation index of water inrush safety in tunnel is taken as the input layer, and the results of the comprehensive risk evaluation are output. The function is sigmoid transform function. The number of hidden layer nodes of the net relative error is determined by the trial calculation method. In the training network process, the original data was divided into 2 groups, and the first 7 groups were trained in the input network, and the data of the last 3 groups were used for the relevant prediction.

Table 5. Detailed survey date

| Tunnel mileage | The development of tunnel surrounding rock fracture | The strength of the surrounding rock layer /m.d-1 | Overlying bedrock fracture zone to the roof /m | The overlying water is rich in water /L(h.m) | Overlying water pressure /Mpa | Tunnel embedment depth /m |
|----------------|---------------------------------------------------|------------------------------------------------|-----------------------------------------------|---------------------------------------------|-----------------------------|--------------------------|
| YDK22+476      | 3                                                 | 0.0025                                         | 5                                             | 0.09                                        | 0.019                        | 19                       |
| YDK22+625      | 5                                                 | 0.0016                                         | 9                                             | 0.16                                        | 0.023                        | 26                       |
| YDK22+765      | 9                                                 | 0.00075                                        | 3                                             | 5.34                                        | 0.015                        | 23                       |
| YDK22+895      | 3                                                 | 0.0006                                         | 16                                            | 3.58                                        | 0.039                        | 29                       |
| YDK22+986      | 4                                                 | 0.0005                                         | 15                                            | 0.76                                        | 0.018                        | 25                       |
| YDK23+136      | 6                                                 | 0.00035                                        | 19                                            | 0.85                                        | 0.029                        | 28                       |
| YDK23+265      | 8                                                 | 0.0032                                         | 8                                             | 5.62                                        | 0.035                        | 18                       |
| YDK23+414      | 9.5                                               | 0.0012                                         | 16                                            | 1.63                                        | 0.028                        | 26                       |
| YDK23+556      | 3                                                 | 0.00086                                        | 4                                             | 0.08                                        | 0.019                        | 17                       |
| YDK23+698      | 7                                                 | 0.00055                                        | 20                                            | 2.63                                        | 0.021                        | 28                       |
Table 6. Comprehensive assessment of water inflow into tunnel

| Serial number | X1   | X2   | X3   | X4   | X5   | X8   | I     | Risk level |
|---------------|------|------|------|------|------|------|-------|------------|
| 1             | 0.168| 0.108| 0.269| 0.125| 0.186| 0.111| 0.168 | B          |
| 2             | 0.6923| 0.8772| 0.7857| 0.9856| 0.6667| 0.8354| 0.7623| B          |
| 3             | 0.0769| 0.5989| 0 | 0.0505| 1.0000| 0.6296| 0.3398| D          |
| 4             | 1.0000| 0.4681| 0.9554| 0.3682| 0.0000| 1 | 0.6326| C          |
| 5             | 0.8462| 0.3368| 0.9404| 0.8773| 0.8750| 0.7737| 0.7898| B          |
| 6             | 0.5385| 0 | 0.9907| 0.8610| 0.4167| 0.9506| 0.6476| C          |
| 7             | 0.2308| 1 | 0.7321| 0.0000| 0.1667| 0.1317| 0.3893| D          |
| 8             | 0.0000| 0.7954| 0.9554| 0.7202| 0.4583| 0.8354| 0.6109| C          |
| 9             | 1.0000| 0.6658| 0.2857| 1.0000| 0.8333| 0 | 0.5968| C          |
| 10            | 0.3846| 0.4083| 1 | 0.5397| 0.7500| 0.9506| 0.6902| B          |

Table 7. Hidden layer node trial

| Number of nodes | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|-----------------|---|---|---|---|---|---|----|----|----|
| Network error   | 0.129 | 0.072 | 0.108 | 0.026 | 0.116 | 0.053 | 0.095 | 0.013 | 0.003 |
| Relative error/%| 2.63 | 1.59 | 2.06 | 1.09 | 2.49 | 1.32 | 1.83 | 0.87 | 0.52 |

Table 8. Training results

| Sequence number | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|-----------------|---|---|---|---|---|---|---|
| Training results| 0.7049 | 0.7626 | 0.3397 | 0.6334 | 0.7893 | 0.6479 | 0.3887 |
| Desired output  | 0.7053 | 0.7623 | 0.3398 | 0.6326 | 0.7898 | 0.6476 | 0.3893 |
| Relative error/%| 0.06 | 0.04 | 0.03 | 0.13 | 0.06 | 0.05 | 0.15 |

Through formula (15), the network hidden layer node is calculated, and the hidden layer node number of the cumulative error is selected as the hidden layer node number of BP network [12].

\[ a = \sqrt{1 + n + m}. \]  

(15)

In the formula: \( m \) takes the constant of 1-10, and \( i \) is the number of input layer nodes and \( n \) is the number of nodes in the output layer.

The sample is calculated according to formula (15), and the number of nodes with the minimum network error is the number of hidden layers. The trial calculation process is shown in Table 7, and the number of hidden layer nodes is 12 according to Table 7. Input the raw data to train the neural network, and the training results are shown in Table 8. After the training, the prediction sample was input into BP neural network, and the risk level prediction results and expert classification results were shown in Table 9.

Table 8 shows that the neural network of training is convergent and the simulation accuracy is higher. Table 9 shows that the maximum error between the result and expected value of the model is
within 3%, and the risk ranking is consistent with that of the experts, indicating that the BP neural network is used to predict the risk of water inflow into tunnel.

| Serial number | 8    | 9    | 10   |
|---------------|------|------|------|
| Predicted results | 0.6146 | 0.5791 | 0.6756 |
| Desired output | 0.6109 | 0.5968 | 0.6902 |
| Error/% | 0.61 | 2.97 | 2.12 |
| Risk level | C | C | B |
| Experts sorting | C | C | B |

4. Summary

Based on the analytic hierarchy process (AHP), the related factors and the importance of the risk of water inflow into mountain tunnel were studied. The results showed that the most significant factors were the distribution of the surrounding rock fracture, the overlying water pressure, the strength of the overlying aquifer, the water-rich degree of overlying, the depth of tunnel, and the distance from the bedrock to the roof. The second is the tunnel excavation method and the construction standard. The last are the tunnel radius and the tunnel spacing.

According to the related factors affecting the risk of water inflow into tunnel, combining analytic hierarchy process (AHP) and BP neural network, the comprehensive evaluation model for risk of water inflow into tunnel is established. This model can obtain a scientific evaluation for the risk of water inflow, construction risk prediction effectively, and reduce the loss caused by the water disaster. It is the first time to integrate the hierarchy process and BP's neural network to build the integrated model for the risk assessment and prediction of water inflow into tunnel. The prediction results were compared with the actual results and the usability and accuracy of the evaluation model were effectively proved. This study provided a new way for risk assessment and prediction for water inflow into tunnel.

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