Application Pigeon Swarm Intelligent Optimisation BP Neural Network Algorithm in Railway Tunnel Construction

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***Abstract*—Due to the uncertainty and complexity of the risk factors of the urban railway tunnel project to increase the difficulty of risk analysis, so that the traditional risk assessment methods can not accurately assess the construction risk of the urban railway tunnel project. Aiming at the problems of the existing risk assessment algorithms, the construction risk assessment method of an urban railway tunnel project based on intelligent optimisation algorithm and machine learning algorithm is proposed. Firstly, for the problem of construction risk identification and assessment of municipal railway tunnel project, a tunnel construction risk identification and assessment scheme using a combination of intelligent optimization algorithm and machine learning algorithm is designed, and the principles and functions of each module of the risk assessment system are introduced; then, for the problem of risk assessment construction, a risk assessment algorithm based on the swarm intelligent optimization algorithm to improve the BP neural network is proposed; secondly, relying on the Hangzhou Secondly, relying on Xinfeng Road underground passage close to cross the underground line 9 tunnel and the side through the Hanghai intercity tunnel project in Hangzhou, the effectiveness of the construction risk assessment algorithm is verified from monitoring data and numerical simulation, and the risk control scheme is proposed in turn. The experimental results show that the risk assessment algorithm proposed in this paper effectively solves the problem of construction risk assessment of the urban railway tunnel project, and improves the prediction performance of the risk assessment algorithm, and verifies that the risk control scheme meets the construction safety requirements.**

Keywords—Municipal railway tunnel construction optimization; scenario risk assessment; machine learning; pigeon flock optimisation algorithm

I. Introduction

With the rapid development of national economy as well as the improvement of information technology, the pace of urbanisation in China is getting faster and faster, which makes the city scale and population grow dramatically [1], and brings a lot of dilemmas to the urban traffic, including traffic congestion, air pollution, and high energy loss [2]. In order to alleviate this development trend, the development of urban underground space to alleviate the surface eyes, improve urban transport, less urban environmental pollution, and achieve carbon neutrality [3]. In addition to making full use of urban space, underground rail transport has the advantages of fast running speed, large passenger capacity, safety and comfort, punctuality, energy saving and environmental protection, but there are also frequent phenomena of accidents in underground tunnel engineering, such as ground subsidence, sand gushing out, and river water backing up [4].

The risk assessment of the optimisation scheme for urban railway tunnel construction not only provide a more accurate, professional and simplified decision-making basis for the decision-makers of the project, but also help to formulate effective risk countermeasures, and is also conducive to the improvement of the risk management level of urban railway tunnel construction [5]. Therefore, the study of risk assessment algorithms for the construction of urban railway tunnel projects is of great theoretical significance and practical problem-solving significance. Risk assessment algorithm generally includes risk mechanism analysis, risk identification, risk assessment and risk evaluation steps [6]. Risk mechanism is generally analysed from a systematic and professional point of view [7], risk identification is mainly to select and classify the uncertain factors that cause adverse consequences of engineering construction [8], risk assessment is mainly to estimate the identified risks, and risk evaluation is to determine the level of risk through qualitative analysis, quantitative analysis or other methods [9]. The risk assessment research of the tunnel engineering construction optimisation scheme for the city railway mainly includes the tunnel engineering construction risk assessment index system and model construction. The index system research generally adopts SWOT analysis method, flow chart method, cause and effect analysis diagram, work decomposition structure method, accident tree method, etc. [10]. Risk assessment model construction research generally uses fuzzy logic method, grey model, machine learning and other methods [11]. With the development of artificial intelligence technology, risk assessment based on machine learning algorithms has entered the field experts and scholars [12]. Due to the uncertainty, hidden nature and complex structure of the construction risk of the municipal railway tunnel project, which makes the non-linear relationship between the risk assessment indicators and the evaluation level, the machine learning method is not only convenient and effective in constructing the mapping relationship between the risk assessment indicators and the evaluation level, but also improves the efficiency of the risk identification and assessment [13]. Risk assessment methods based on machine learning algorithms for the construction of municipal railway tunnel projects include BP neural networks, support vector machines, decision trees, clustering and other

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algorithms [14]. Although the research on construction risk assessment of municipal railway tunnel projects has achieved certain results, research and analysis are still needed in the area of construction risk assessment of cross operation tunnels on top of the pipe. Although the pipe jacking method has been used more often in underground engineering construction, it faces the problem of construction control that threatens the structural safety when the pipe jacking crosses the existing structure [15]. The construction of pipe jacking will cause disturbances such as loading and unloading, changing pore water pressure, and changing stratum compactness to the soil body, destroying the state of stress equilibrium, and in the long term, it will cause deformation of stratum consolidation, which will result in the synergistic deformation of the existing structure and the stratum [16], so it is very meaningful to study the construction risk identification and assessment methods, and the optimal control of the construction risk of the tunnel spanning over the operation of the jacking pipe. Through the domestic and foreign literature research and analysis, there is a certain accumulation of construction risk assessment research for the top tube of urban railway cross operation tunnel, but there are still many problems [17]:

- Less risk research and more construction technology research, and lack of construction overall risk research;
- Lack of reliability of the risk identification process;
- Quantitative analysis of the risk assessment is not in-depth enough;
- Application of the results of the risk assessment is low. The applicability of the results is low.

This paper focuses on the risk assessment of tunnel construction on top of pipe, combines machine learning algorithm and pigeonhole optimisation algorithm, and constructs a risk assessment method based on pigeonhole optimisation algorithm and improved BP neural network. Aiming at the characteristics of the risk assessment problem of tunnel construction above the top tube, a risk assessment scheme for tunnel construction is designed, and the roles of each module of the risk assessment system and its principle are introduced in detail. Combined with the risk assessment scheme and the assessment model construction algorithm, the effectiveness of the risk assessment model is studied and the performance impact of the risk control measures is analysed for the case of the operation tunnel project of Metro Line 9 in the silt stratum of Linping District, Hangzhou City.

II. Design of a Risk Identification and Assessment Programme for Tunnel Construction

A. Programme Design

In order to improve the reliability of the risk identification and assessment method of the construction risk of the pipe jacking up and across the operation tunnel and optimise the feasibility of the risk control scheme, this paper studies the tunnel construction risk identification and assessment scheme using a combination of intelligent optimisation algorithms and machine learning algorithms [18], which is shown in Fig. 1.

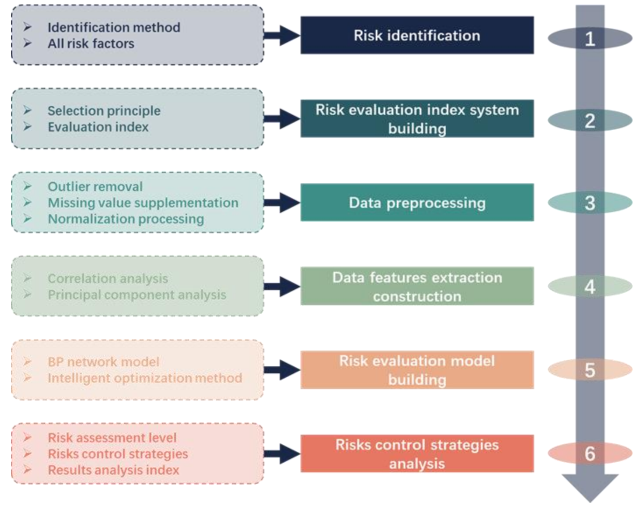


Fig. 1. General scheme of risk assessment for tunnel construction.

From Fig. 1, in the construction risk assessment scheme of the top tube over operation tunnel based on the intelligent optimization algorithm combined with the machine learning algorithm, the mechanism of the analysis of the construction process of the top tube over operation tunnel is analysed, and the sources of risk faced by the construction process are identified by combining with the method of the decomposition structure of the work; in order to further improve the accuracy of the construction risk assessment model of the top tube over operation tunnel, the raw data continue to be pre-processed, and the operations of outliers elimination, missing values supplementation and normalization are carried out. In order to further improve the accuracy of the construction risk assessment model, the raw data are preprocessed, and operations such as outlier removal, missing value supplementation, and normalisation are carried out. In addition, in order to reduce the redundancy of the indicator system and improve the efficiency of the model construction, correlation analysis and dimensionality reduction analysis are carried out for the input indicators; on the basis of the data preprocessing and analysis, the intelligent optimisation algorithm proposed in this paper is combined with the improvement of machine learning algorithm to realise the construction and optimisation of the risk assessment model of the construction of the roof tube above the operating tunnels; According to the risk assessment level and risk probability and control measures, numerical analysis and monitoring analysis are carried out on the proposed deformation control scheme for the construction of roof tube over operation tunnel.

B. Module Analysis

The research on construction risk assessment method of header tube over operation tunnel based on intelligent optimization algorithm and improved machine learning algorithm mainly includes construction risk identification of header tube over operation tunnel, establishment of construction assessment index system of header tube over operation tunnel, processing and analysis of measurement value of header tube over operation tunnel construction risk assessment index, optimization of construction risk assessment model of header tube over operation tunnel and analysis of the results of the risk control scheme. technical research [19], the specific research composition framework is shown in Fig. 2. In Fig. 2, the construction risk assessment system of top tube over operation tunnel based on intelligent optimization algorithm and improved machine learning algorithm is mainly composed of risk identification, indicator system, risk level, data processing, risk assessment, risk control and other modules in order to accurately and objectively and systematically assess the construction risk of top tube over operation tunnel and deformation control scheme.

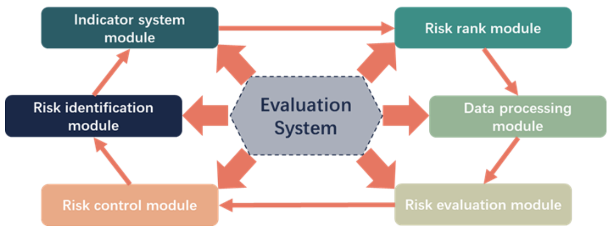


Fig. 2. Risk assessment system building blocks.

1) Risk identification module: The risk identification module identifies and categorises the uncertainties that may cause adverse consequences during the construction of the tunnel, and then screens out the uncertainties that may cause risky accidents. As an important basis for risk management, the risk identification module can determine the impact of different risk factors on the construction of the tunnel above the pipe, and then classify the different risk factors into categories, and the process of line identification is demonstrated in Fig. 3. The inputs of the risk identification module of the construction project of the roof tube over operation tunnel are investigation data analysis, expert consultation, experimental demonstration, and work decomposition structure method, and the outputs are risk code, risk factors, risk events, and risk consequences, and the specific input-output relationship diagram is presented in Fig. 4.

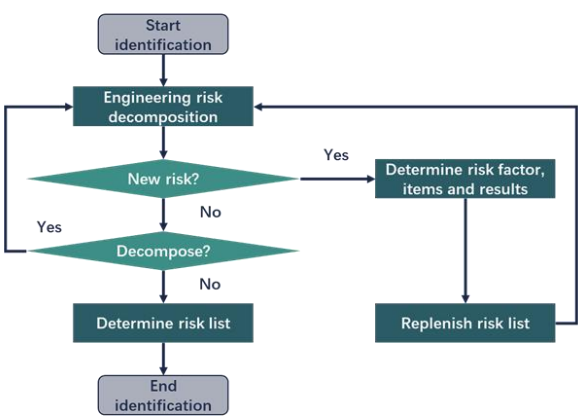


Fig. 3. Risk assessment system building blocks.

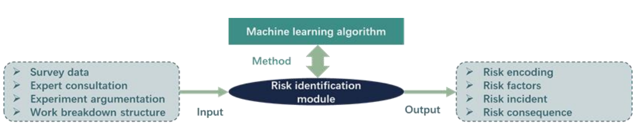


Fig. 4. Risk identification input-output relationship.

2) Indicator system module: When constructing the construction risk assessment index system of the roofed pipe upper span operation tunnel, it is necessary to follow some basic principles, including the principles of systematicity, scientificity, operability, comparability, etc., as shown in Fig. 5.

Fig. 5. Principles for the selection of risk assessment indicators.

On the basis of the identification and classification results of the construction risk of the top tube over operation tunnel, the index system module integrates the field survey and the research of the field research experts, and adopts the methods of quantitative analysis, qualitative analysis, and case study, etc., and constructs the construction risk of the top tube over operation tunnel from the aspects of engineering geological risk A, investigation and design risk B, construction technology risk C, tunnel engineering risk D, management risk E, and environmental factor risk F. Assessment index system, the specific system structure is shown in Fig. 6. As can be seen from Fig. 6, the input of the indicator system module is the selection principle and risk identification results, and the output is the risk assessment indicator system, and the input-output relationship is shown in Fig. 7.

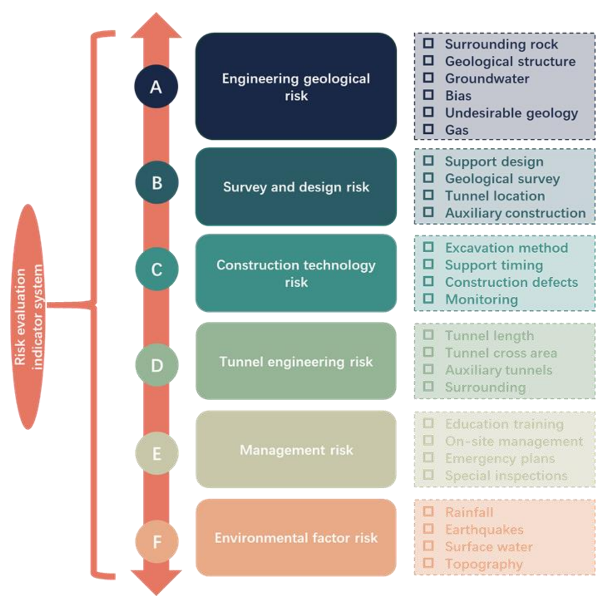


Fig. 6. Risk assessment index system for construction of pipe jacking over operational tunnels.

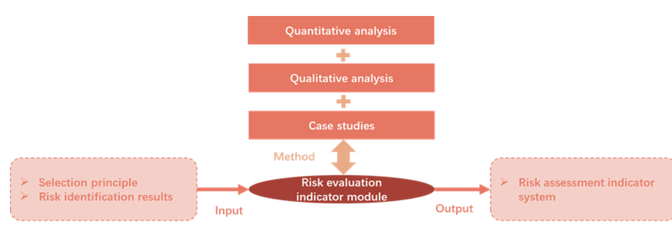


Fig. 7. Principles for the selection of risk assessment indicators.

3) Data processing module: The data processing module includes processes such as outlier removal, missing value supplementation, normalisation, indicator feature correlation analysis, feature dimensionality reduction, etc., as shown in Fig. 8.

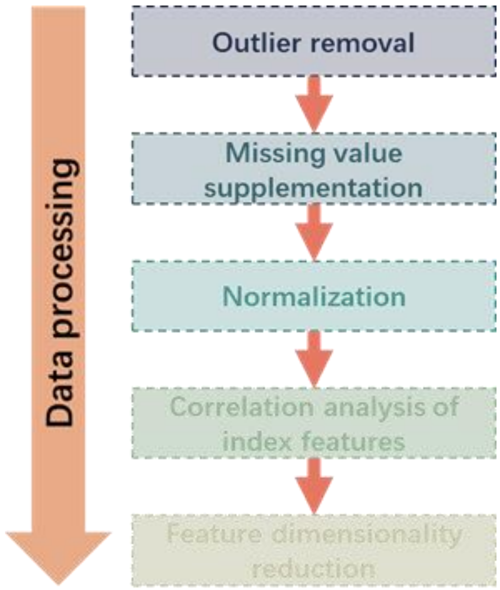


Fig. 8. Data pre-processing flow.

As an important step in data preprocessing, outlier removal removes data points that significantly deviate from other values in the data set. In this paper, we use the outlier processing method based on the 3σ criterion [20], which determines any data point in the data that is outside the range of the mean ± 3 standard deviations as an outlier, and the principle is shown in Fig. 9.

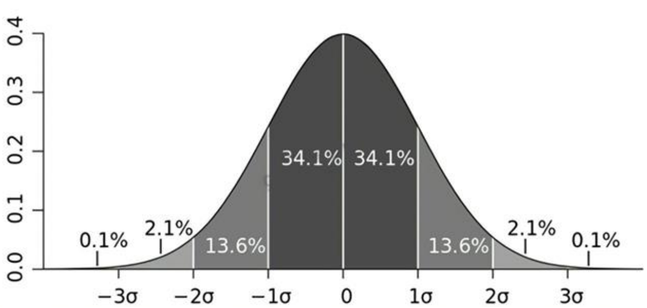


Fig. 9. Outlier rejection algorithm based on 3σ criterion.

In the case of missing data, the missing value supplementation can fill in the data, make the data conform to the pattern, and improve the data quality to improve the performance of the subsequent evaluation model. In this paper, we adopt the proximity filling method, i.e., we use the observations before or after the missing values to fill in the missing values, as shown in Fig. 10.

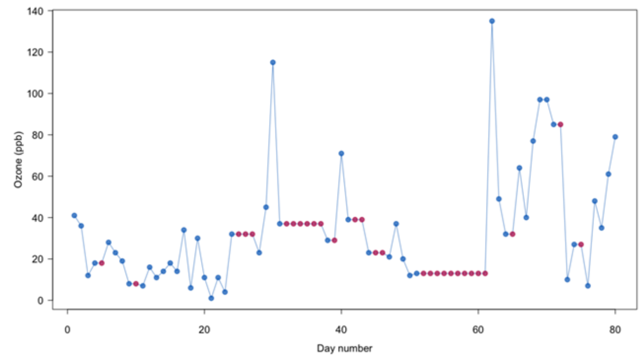


Fig. 10. Algorithm for missing value filling method.

In order to eliminate the variance over the limit brought about by the data magnitude, the normalisation process is to scale the data so that it falls into a small specific interval. For the data characteristics occurring in the construction of the top tube up-span operation tunnel, this paper adopts the *Z*-score normalisation method, i.e., all data are normalised to the range of normal distribution with mean 0 and variance 1, and the calculation formula is as follows Eq. (1):

$$x' = \frac{x - \bar{x}}{\sigma} \tag{1}$$

Where x' denotes the data after normalisation, x is the data before normalisation, $\bar{x}$ is the mean and σ is the standard deviation.

In order to analyse the redundancy of the risk assessment indicators for the construction of the roof-tube up-and-over operational tunnels, Pearson is used in this paper to calculate the correlation coefficients, which are calculated as follows, Eq. (2):

$$\rho(x, y) = \frac{\operatorname{cov}(x, y)}{\sigma(x) \cdot \sigma(y)} = \frac{E\left[(x - \mu_x)(y - \mu_y)\right]}{\sigma(x) \cdot \sigma(y)} \tag{2}$$

Where $\operatorname{cov}(x, y)$ is the covariance coefficient and $\sigma(x)$ and $\sigma(y)$ are the standard deviations.

In order to reduce the dimensionality of the construction risk assessment indexes of the roof-tube up-and-over operation tunnels and extract the principal components, this paper adopts the Kernel Principal Component Analysis (KPCA) [21] method to extract features and reduce the dimensionality of the input construction risk assessment indexes. The KPCA is an improvement of the Principal Component Analysis (PCA) method, which uses the kernel function to construct complex nonlinear classifiers. The core idea of KPCA is to use the kernel function to map the original data to a high-dimensional feature space, and then perform PCA in that space. The specific principle is shown in Fig. 11.

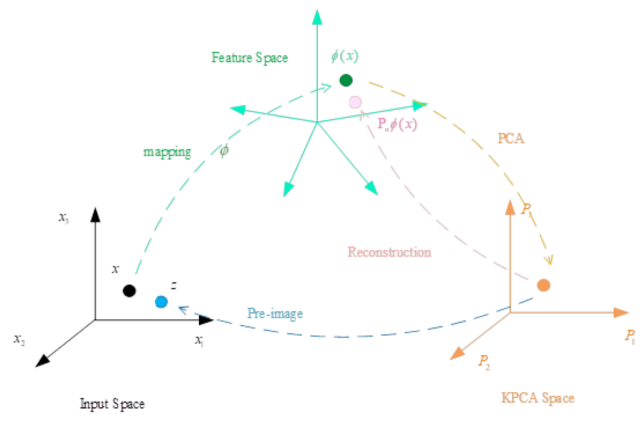


Fig. 11. Principle of KPCA method.

According to the introduction of the principles and mechanisms of the above methodology, the input to the data processing module consists of the original values of the construction risk assessment indicators for the jacked-up cross operational tunnels, and the output is the standardised values of the downgraded assessment indicators.

4) Risk level module: According to the risk assessment index system of the construction risk of pipe jacking up and across the operation tunnel, including engineering geological risk A, investigation and design risk B, construction technology risk C, tunnel engineering risk D, management risk E and environmental factors risk F and other six aspects of the 26 assessment indicators, this paper adopts the AHP to initially determine the weight of the indicators, and the specific process is shown in Fig.12.

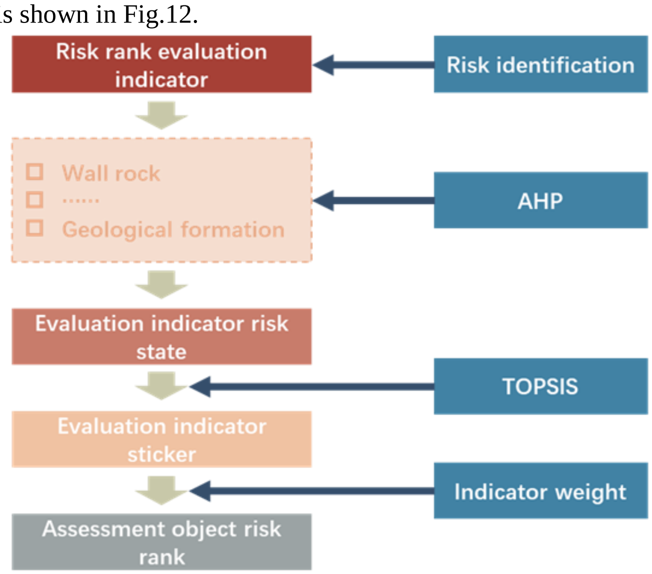


Fig. 12. Flowchart for the initial determination of the overall risk level based on the hierarchical analysis method.

In order to determine the degree of risk impact based on the risk level, so as to determine the risk control strategy, this paper classifies the risk level of the construction of pipe jacking up and across the operation tunnel into five types, which are high risk, higher risk, medium risk, lower risk and low risk, and the scores corresponding to the different risk levels are shown in Table I.

TABLE I. DIFFERENT RISK LEVELS AND CORRESPONDING LEVEL SCORES

Risk level	High	Higher	Moderate	Lower	Low
Score	≥20	15-20	10-15	5-10	0~5

The inputs to the risk level module are the hierarchical analysis method, the indicator system, and the outputs are the classification of the levels and the determination of the level scores.

5) Risk assessment module: According to the risk analysis data of the construction risk of the top tube over the operation tunnel, the machine learning algorithm is used to determine the mapping relationship between the value of the construction risk assessment indexes of the top tube over the operation tunnel and the value of the risk assessment level, so as to construct the risk assessment model of the construction risk of the top tube over the operation tunnel. With the increase of data volume, the machine learning model structure optimisation and parameter optimisation are prone to problems such as premature maturity, falling into local optimum, and slow convergence speed. In order to improve the performance of the machine learning algorithm, an intelligent optimisation algorithm is used to optimise it [22], and the improved paradigm is shown in Fig. 13.

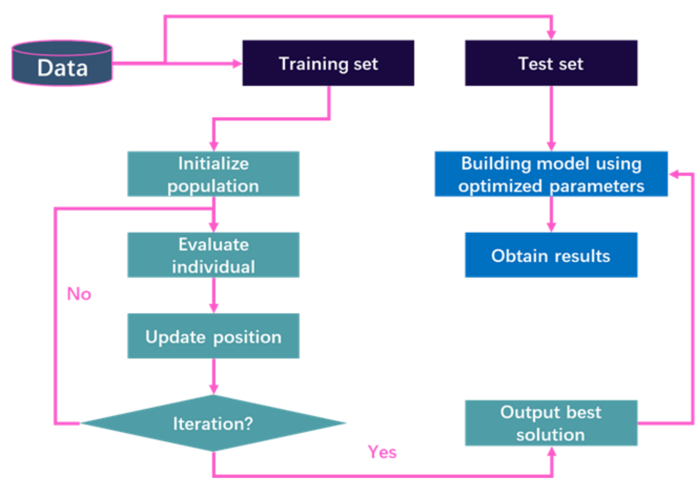


Fig. 13. Machine learning algorithm optimisation.

In Fig. 13, the first step is to determine whether the machine learning algorithm needs to optimise the structural parameters or the control parameters, and the machine learning algorithm chosen in this paper is the BP neural network, so the variables to be optimised are the structural parameters, i.e., the BP neural network weights and biases. According to the initialisation strategy to initialise the BP neural network weights and bias, with the training error as the value of the fitness value function value, the optimisation strategy of the intelligent optimisation algorithm is used, and after iteration, the BP neural network weights and bias with the smallest error are obtained.

The inputs to the risk assessment module are BP neural networks, intelligent optimisation algorithms, risk analysis data for the construction of a roof-tube up and over an operational tunnel, and the outputs are the predicted risk level scores as well as the levels.

6) Risk control module: The risk control module will remove accident risk control measures from engineering geology, construction technology, engineering management and other aspects according to the risk assessment results and risk acceptance criteria. In view of the construction risk problem of pipe jacking up and across operation tunnels, this paper analyses the deformation risk of pipe jacking through operation tunnels, and gives the deformation control method, i.e., the risk control measures are given from the engineering technology level.

III. Improved Machine Learning Algorithms for Risk Assessment Problems

A. Machine Learning Algorithms

Machine learning algorithms are a subfield of artificial intelligence that allow computers to learn from data and improve their performance without the need for explicit programming instructions. These algorithms can be categorised into three types, including supervised learning, unsupervised learning and reinforcement learning, as shown in Fig. 14. Since the problem of risk assessment for the construction of a roofed pipe up and over operational tunnels is a supervised learning problem, machine learning algorithms in the supervised learning category are used in this paper.

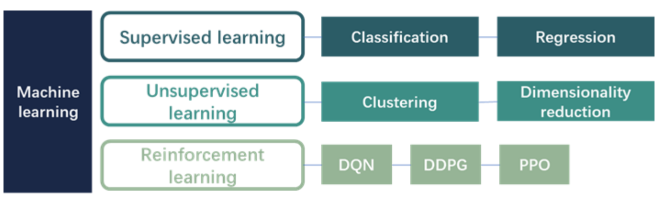


Fig. 14. Machine learning algorithm classification.

Common machine learning algorithms include linear regression, logistic regression, decision trees, random forests, K-nearest neighbours, Bayesian networks, neural networks, support vector machines, and integrated learning [23], as shown in Fig. 15.

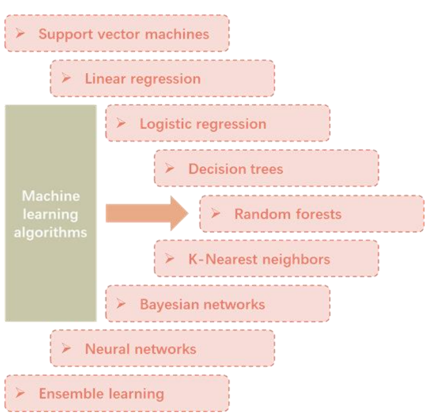


Fig. 15. Types of machine learning algorithms.

B. BP Neural Network

1) Principles and mechanisms: BP neural network [24] consists of three layers: input layer, hidden layer and output layer. W_{mi}, W_{in} The connection weights from the input layer x_m to the hidden layer k_i and the connection weights from the hidden layer k_i to the output layer y_n are represented respectively.

Define the actual output of the network as Eq. (3):

$$Y(s) = (v_N^1, v_N^2, \ldots, v_N^N) \tag{3}$$

Its desired output is Eq. (4):

$$d(s) = (d_1, d_2, \ldots, d_N) \tag{4}$$

a) Positive propagation of the input signal

The output of the m th neuron of layer I can be expressed as Eq. (5):

$$v_M^m(s) = x(s) \tag{5}$$

The inputs u_I^i and outputs v_I^i of the i th neuron of layer H are defined respectively as

$$u_I^i(s) = \sum_{m=1}^{M} w_{mi}(s) v_M^m(s) \tag{6}$$

$$v_I^i(s) = f\left(u_I^i(s)\right) \tag{7}$$

In Eq. (6) and Eq. (7), where $f(\cdot)$ denotes the H-layer transfer function.

Then the input u_N^n and output v_N^n of the n th neuron of layer O can be expressed as Eq. (8) and Eq. (9):

$$u_N^n(s) = \sum_{n=1}^{N} w_{in}(s) v_I^i(s) \tag{8}$$

$$v_N^n(s) = g\left(u_N^n(s)\right) \tag{9}$$

where $g(\cdot)$ denotes the output layer transfer function.

Then the overall error of the network can be expressed as Eq. (10):

$$e(s) = \frac{1}{2}\sum_{n=1}^{N} e_n^2(s), e_n(s) = d_n(s) - v_N^n(s) \tag{10}$$

b) Error signal back propagation

When the overall system error is greater than a threshold, the weights need to be adjusted so that the error gradually decreases.

$$w_{in}(s+1) = w_{in}(s) + \Delta w_{in}(s) \tag{11}$$

$$w_{mi}(s+1) = w_{mi}(s) + \Delta w_{mi}(s) \tag{12}$$

In Eq. (11) and Eq. (12), Where, $\Delta w_{in}(s)$ denotes the weight adjustment value of H layer and O layer, and $\Delta w_{mi}(s)$ denotes the weight adjustment value of I and H layers.

2) BP network applications: BP networks are able to mimic the learning and memory mechanisms of the human brain to learn and predict input data.BP networks are widely used in a variety of scenarios [25] due to their ability to learn to train nonlinear mapping laws, including but not limited to:

- BP networks are widely used in the field of pattern recognition;
- BP networks can be used to predict future outcomes or to make optimal decisions, such as in finance for predicting stock prices or developing risk management strategies;
- Train neural networks to control the actions of robots or to optimise production processes to improve efficiency;
- In the field of machine translation, BP networks are used to generate high quality translated texts;
- BP networks also perform very well in the field of speech recognition, such as speech to text and voice command recognition.

3) Problems with BP: Although BP networks have a wide range of applications in many fields, it has some problems and challenges:

- Overfitting the training data leads to performance degradation on the test data;
- The optimisation process may fall into local minima without reaching the global optimal solution;
- In deep networks, gradients may fade away during backpropagation, making it difficult for the network to learn.

C. Pigeon Swarm Optimisation Algorithm

Pigeon-Inspired Optimization (PIO) is a novel population intelligence optimization algorithm [26], which is inspired by the autonomous homing behaviour of domestic pigeons in nature. This algorithm is mainly implemented by map and compass operators and landmark operators to update the position and velocity of pigeon flocks, so as to simulate the homing behaviour of domestic pigeons and find the optimal solution.

4) Algorithmic principles

a) Map and compass calculator: In the flock optimisation algorithm, map and compass operators are used to model the behaviour of domestic pigeons that use the geomagnetic field to determine the approximate direction. The velocity and position of each pigeon is updated based on the previous generation's velocity and current optimal position, as shown in Fig. 16. Specifically, the equations for updating the pigeon's velocity is as follows Eq. (13) and Eq. (14):

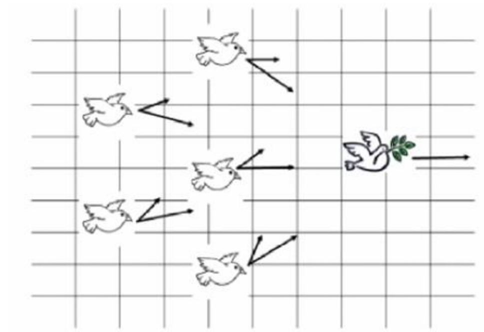


Fig. 16. Map core guide operator.

$$V_i^t = V_i^{t-1} e^{-R\times t} + rand \cdot \left(X_{gbest} - X_i^{t-1} \right) \quad (13)$$

$$X_i^t = X_i^{t-1} + V_i^t \quad (14)$$

Where X_i^t denotes the position information of the i^{th} individual of the flock in the tth iteration, V_i^t denotes the individual velocity information, X_{gbest} denotes the optimal individual position, R denotes the map kernel compass factor, and $rand$ is a random number. When the number of iterations reaches a certain number of iterations, the execution of the map and compass operator stops and enters the landmark operator.

5) Pseudo-code and flowchart: According to the basic principle and optimisation strategy of the pigeon flocking optimisation algorithm, the flowchart of the pigeon flocking optimisation algorithm is shown in Fig. 17 respectively.

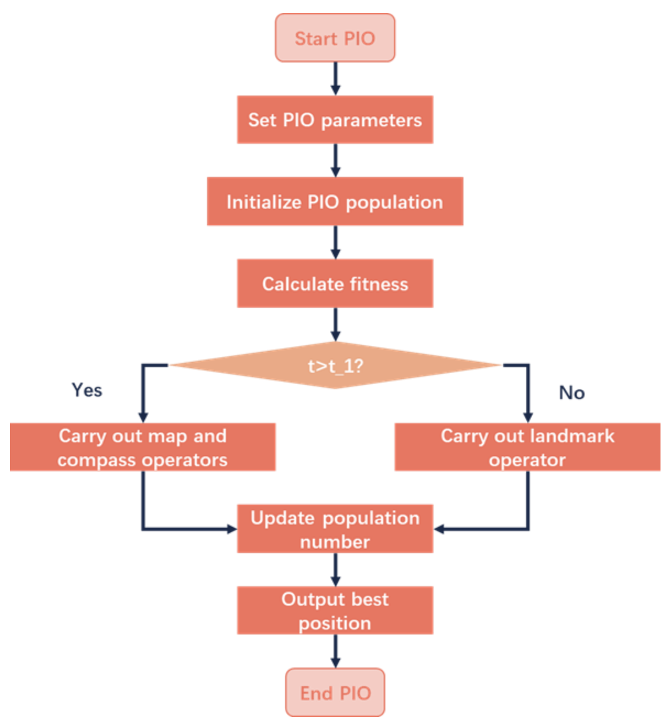


Fig. 17. Flowchart of the PIO algorithm.

D. PIO-BP Neural Network

In this paper, we use real number coding to encode the BP hidden layer weight values and hidden layer bias with the coding dimension of $(m_1 \times l_1 + l_1) + (m_2 \times l_2 + l_2)$, and also use MAE as the adaptation function Eq. (19):

$$MAE = \frac{1}{M} \sum_{i=1}^{M} \left| \hat{y}_i - y_i \right| \tag{19}$$

Where, $\hat{y}_i$ denotes the predicted value based on the proposed algorithm, y_i denotes the true value and M is the number of test samples.

The steps of the PIO-BP neural network prediction method (Fig. 18) are as follows:

- PIO algorithm encodes the initial parameters;
- Calculates the value of the fitness function;
- Updates the position and speed of the PIO population by using the map and compass operator and landmark operator;
- Calculates the value of the fitness function and updates the global optimal solution;
- Determines whether or not the termination conditions are satisfied;
- Decodes the PIO algorithm-optimised BP network structure parameters;
- Constructing a tunnel construction risk assessment model based on PIO-BP neural network.

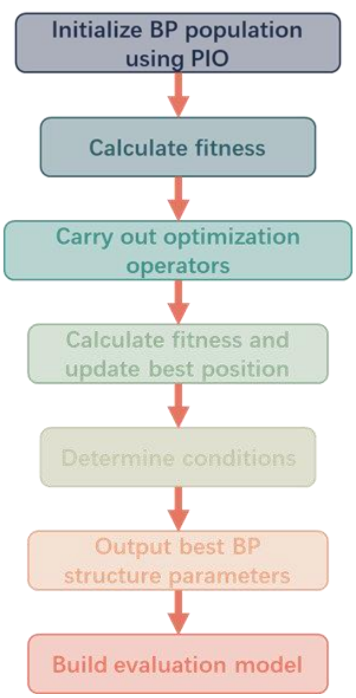


Fig. 18. Tunnel construction risk assessment based on PIO-BP neural network.

- Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as “3.5-inch disk drive”.
- Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.
- Do not mix complete spellings and abbreviations of units: “Wb/m^2” or “webers per square meter”, not “$webers/m^2$”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.
- Use a zero before decimal points: “0.25”, not “.25”. Use “cm^3”, not “cc”. (*bullet list*)

IV. Algorithmic Applications

In order to verify the performance of the risk assessment algorithm for the construction engineering of the city railway tunnel project, this paper relies on the construction risk analysis of the tunnel of Xinfeng Road underground passage close to the upper crossing of Metro Line 9 in Hangzhou and the side penetration of Hanghai Intercity Tunnel Project, constructs the risk assessment model, and puts forward the effective risk control measures.

A. Project Description

Xinfeng Road Underpass in Linping District, Hangzhou is located in the north side of the intersection of Xinfeng Road and Wenzheng Street in Linping District, and there are many existing structures within the new construction scope. The channel passes through Xinfeng Road, the main road (roof pipe depth 2.3m), and close to cross (roof pipe and tunnel structure minimum vertical clearance 2.5m) existing operation Hangzhou Metro Line 9, Yuhang high-speed rail station ~ Nanyuan station interval two-line tunnel, and parallel side through (roof pipe and tunnel horizontal clearance 15.6m) existing Hanghai intercity two-line tunnel. The total length of the underpass is 136.5m, which is constructed by pipe jacking method and open cut method, of which the starting shaft and receiving shaft open cut section are 34.9m and 26.6m long respectively, with the depth of the shaft being about 8~9m. The crossing section of the underpass is constructed by pipe jacking method from west to east, with a length of 75m. the standard rectangle pipe jacking section is adopted, with the internal dimensions of 6.0m×3.3m, the wall thickness of the jacking pipe is 0.45m, and the length of the pipe section is 1.5m, and the socket joint is adopted. The length of the pipe section is 1.5m, and the socket joints are adopted.

B. Construction Risk Assessment

For the factors that may lead to excessive deformation of the existing tunnel during the jacking construction process of the pipe jacking section, the main focus is on the silt layer and the close proximity through the existing tunnel in two aspects: (1) the project is located in the silt layer, with high compressibility, high sensitivity and thixotropy, poor engineering properties, and unfavourable control of deformation of the ground layer disturbed by the construction. At the same time belongs to the low to medium permeability stratum, and this project is adjacent to East Lake, rich groundwater recharge, strata water content is large, jacking process is prone to groundwater gushing, resulting in over-excavation of tunnels and triggering the risk of construction safety; (2) jacking pipe with a vertical clearance of 2.5m through the operating tunnel in the vicinity of the top, jacking process in the front of the strata by the construction of the influence of the stress of the disturbance is serious, resulting in the unloading of the lower part of the front disturbed area as well as the pipe section of the ground below shear disturbance zone During the jacking process, the ground strata in front is severely disturbed by the impact of the application, which causes the unloading disturbance zone in front and the shear disturbance zone in the lower part of the pipe section to be relaxed, and the structure of the operating tunnel in the lower part of the pipe section is uplifted along with the surrounding strata, which has a great impact on the deformation of the existing tunnel before and after jacking. At the same time, the soil cover above the jacking tube is shallow, only 2.3m, and the jacking has a strong influence on the deformation of the ground surface, and the deformation effect of the shallow soil cover will increase the deformation of the tunnel in the unprotected condition.

Aiming at the above key risks, this paper carries out construction risk assessment from engineering geological risk A, investigation and design risk B, construction technology risk C, tunnelling risk D, management risk E and environmental factor risk F. Risk assessment indexes of the six aspects are taken as inputs, and risk level score values are taken as outputs, where the risk index values need to be extracted by downscaling features. According to the risk level score value, the risk level is obtained by combining the correspondence between the risk assessment value and the level grade in the risk level module.

C. Risk Control Programme

The deformation control of pipe jacking through operational tunnels includes deformation monitoring control and factor-specific control. Deformation monitoring and control includes the development of deformation control standards and automated monitoring measures; factor-specific control includes MJS portal-type ground reinforcement measures for the chalky sand stratum close to the underpass and surface hardening measures for shallow overburden.

Standard measures for deformation control were developed as shown in Table II.

TABLE II. DEFORMATION CONTROL STANDARDISATION

Structural safety control indicator control values	metric
Horizontal displacement (mm)	<5
Vertical displacement (mm)	<5
Relative convergence (mm)	<5
Differential settlement at station and zone junction (mm)	<5
Radius of deformation curvature (m)	>15000
relative curvature of deformation	<1/2500
Tube sheet seam opening (mm)	<1
Additional load on outer wall (kPa)	≤10
Crack width (mm)	≤0.1
Contact net guide height (mm)	<20
Roadbed and track displacement (mm)	<5

Aiming at the characteristics of large compressibility, poor engineering properties and large water content of the silt layer, and the large influence of groundwater on the slagging process of the pipe jacking and the stability of the thixotropic mud on the outside of the pipe joints, the all-around high-pressure rotary injection grouting method (MJS) is adopted in the silt layer crossed by the pipe jacking to carry out gated reinforcement in advance in the area of the pipe jacking crossing over the operation tunnel.

V. EXPERIMENTAL ANALYSIS

A. Experimental Set-Up

In order to verify the effectiveness of the risk assessment algorithm for tunnel construction proposed in this paper and the feasibility of taking risk control measures, this paper takes the data of the project of Hangzhou Xinfeng Road underground passage close to crossing the metro line 9 tunnel and side through Hanghai intercity tunnel as the data for analysis, and selects SVM, Decision Tree, and BP as the comparative algorithms of the analysis and assessment algorithms of the PIO-BP neural network, and at the same time analyses the risk control measures from the on-site monitoring and numerical simulation. Two aspects of risk control measures are analysed.

The algorithm setup is shown in Table III. The algorithm used in this paper is PIO-BP neural network and the comparison algorithms are SVM, Decision Tree and BP neural network.

TABLE III. PARAMETER SETTINGS FOR THE COMPARATIVE RISK ASSESSMENT ALGORITHM

Arithmetic	Parameterisation
Support Vector Machine (SVM)	C=100,σ=0.1
Decision Tree	The maximum number of divisions is 4
BP neural network	Hidden layer node is 50, activation function is radial basis function
PIO-BP neural network	Hidden layer nodes are 50, activation function is radial basis function, population size is 50, maximum number of iterations is 100

The experimental simulation environment is Windows 10, the risk assessment algorithm programming language Python 3.7, and the Midas GTS finite element software is used for the risk control measures.

The experimental finite element calculation model for numerical analysis of risk control measures is shown in Fig. 19. x is the direction of pipe jacking and z is the direction of model elevation. The relevant calculation parameters of each soil layer are shown in Table IV The pipe jacking sheet and tunnel structure, station wall panel structure, enclosure structure and support adopt linear elastic principal structure, and the values of structural parameters are shown in Table V.

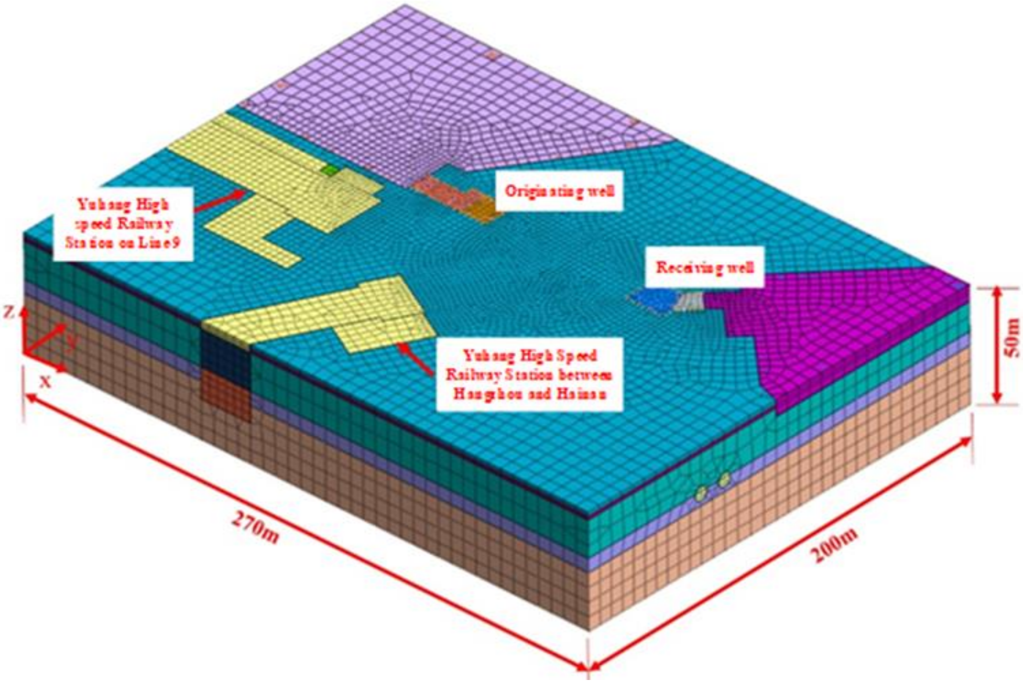


Fig. 19. Schematic diagram of finite element calculation model.

TABLE IV. CALCULATED PARAMETERS FOR SOIL LAYERS

Stratigraphic name	Triaxial loading stiffness E_{50} (MPa)	Triaxial unloading stiffness E_{ur} (MPa)	Consolidator loading stiffness E_{ord} (MPa)	Initial small strain modulus G_0 (MPa)	Modulus stress related power index(m)	Shear strain level $\gamma^{0.7}$
miscellaneous fillings	3.0	15.0	3.0	50.0	0.5	1.0×10^{-4}
clayey silt	7.0	28.0	7.0	112.0	0.5	2.0×10^{-4}
sandy silt	8.5	34.0	8.5	136.0	0.5	2.0×10^{-4}
silt sand	10.0	40.0	10.0	160.0	0.5	2.0×10^{-4}
clays	6.5	27.0	5.4	108.0	0.7	2.0×10^{-4}

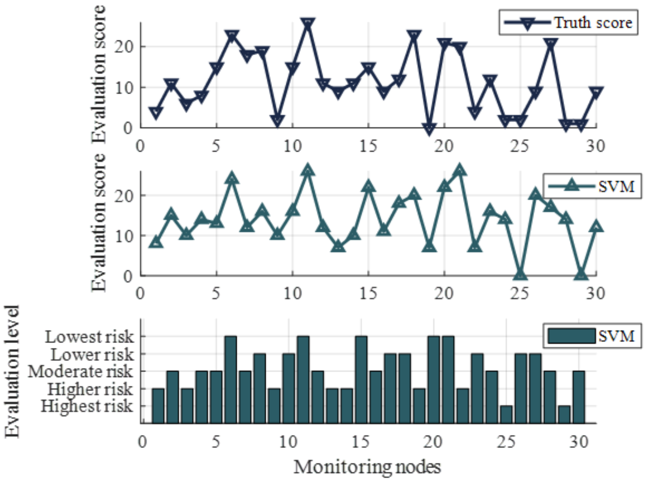
TABLE V. STRUCTURAL CALCULATION PARAMETERS

Typology	Serious (kN/m)^3	Modulus of elasticity (Mpa)	Poisson's ratio	Cohesion(kPa)	Angle of internal friction(°)
MJS plus solids	18.0	400	0.2	1000	23
pipe jacking slice	25.0	34500	0.25	-	-
shield	25.0	34500	0.25	-	-
Station wall panels, enclosures and internal supports	24.0	30000	0.2	-	-
steel support	78.0	200000	0.2	-	-

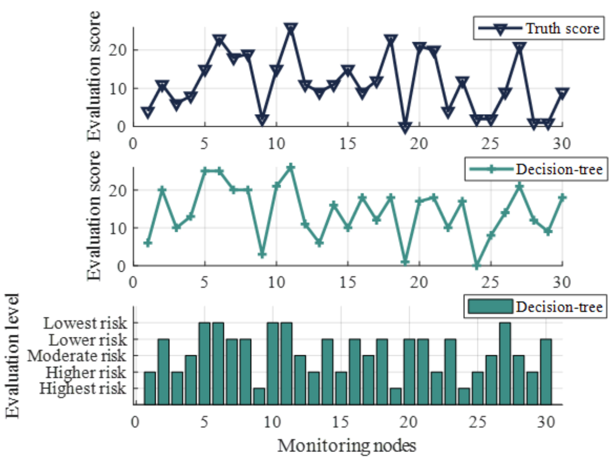
B. Analysis of Evaluation Test Results

In order to verify the effectiveness of the PIO-BP neural network based risk assessment algorithm for tunnel construction, this subsection compares the performance of SVM, Decision-tree, BP, and PIO-BP methods using a test set.

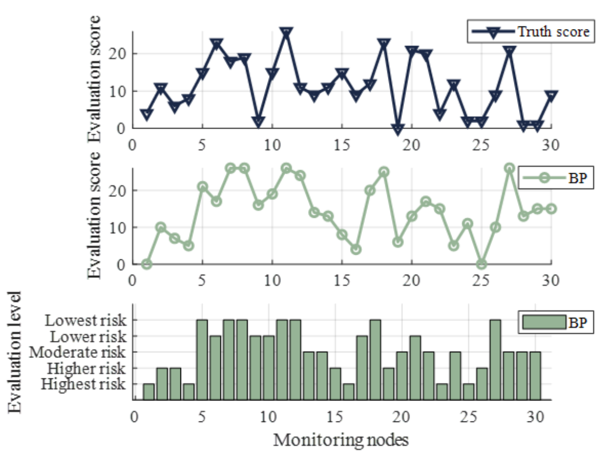
The results of risk assessment of 26 monitoring sections in tunnel construction based on different algorithms are given in Fig. 20. As can be seen from Fig. 20(a) – Fig. 20(d), the accuracy of the risk assessment algorithm of the PIO algorithm optimised BP neural network is better than the other algorithms. The statistical results show that the risk assessment model based on the PIO-BP algorithm is closer to the real value of the test set data than the assessment results of other modelling methods, which demonstrates the high assessment accuracy of the model.



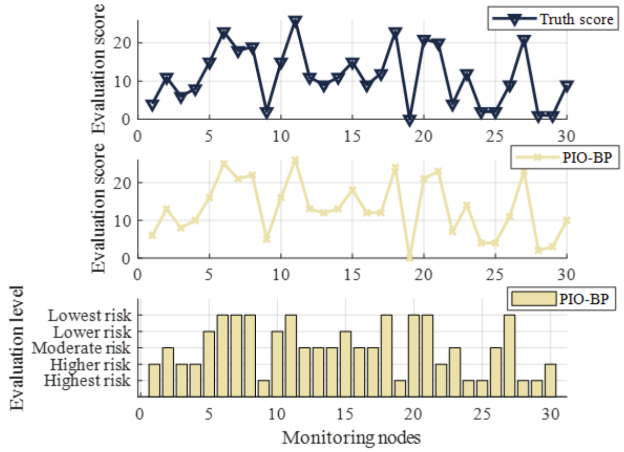
(a) SVM



(b) Decision-tree



(c) BP

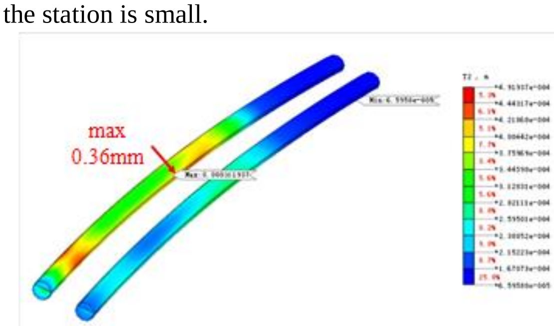


(d) PIO-BP

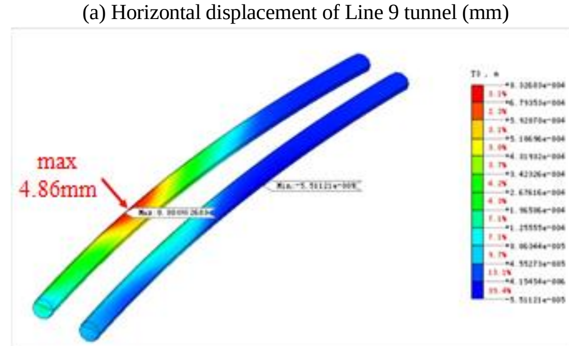
Fig. 20. Test results of different risk assessment model algorithms.

C. Analysis of the Results of the Testing of Risk Control Measures

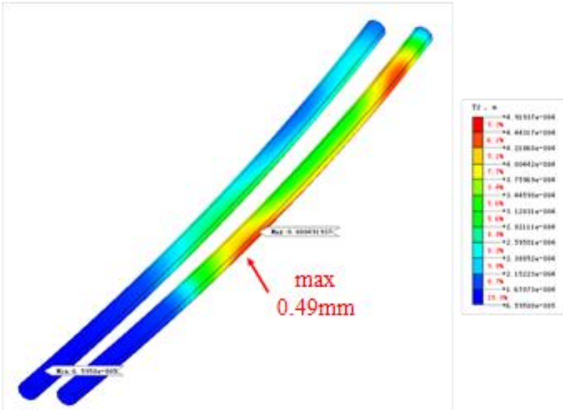
6) Tunnel structural displacement: The software is used to simulate the pipe jacking construction, and the calculation results after the advancement of the pipe jacking in the characteristic working condition are shown in Fig. 21. It can be seen from Fig. 21 that the deformation values of the two operating tunnels satisfy the control requirement of 5mm. The difference settlement at the junction between the tunnel section and the station is small.



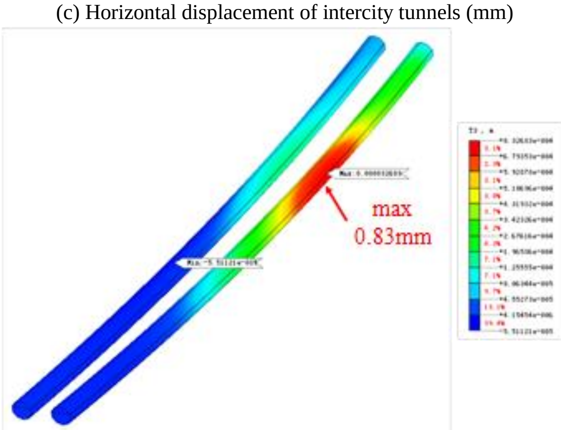
(a) Horizontal displacement of Line 9 tunnel (mm)



(b) Vertical displacement of Line 9 tunnel (mm)



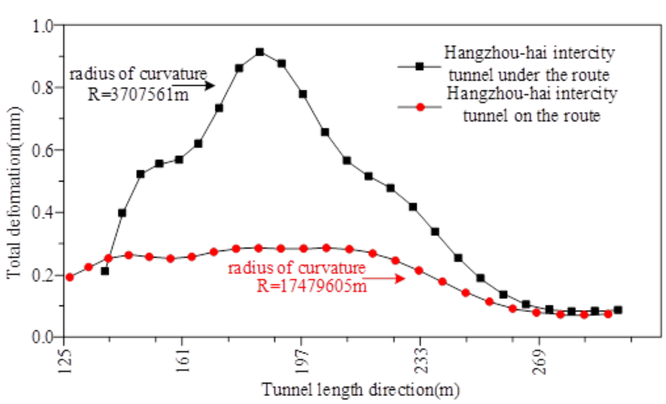
(c) Horizontal displacement of intercity tunnels (mm)



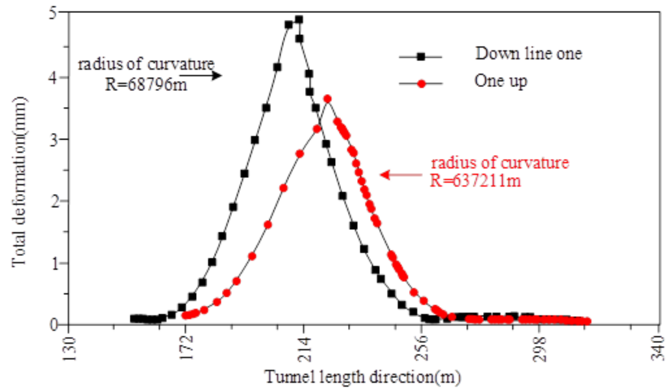
(d) Vertical displacement of intercity tunnels (mm)

Fig. 21. Pipe jacking to complete the upper span construction results.

7) Tunnel structural curvature: According to the maximum deformation results of the two tunnels, the additional radius of curvature of the tunnels caused by the jacking is calculated, and the results are shown in Fig. 22. It can be seen that the additional radius of curvature of the two operation tunnels caused by the jacking construction is much larger than the control requirements of 15,000m, which meets the requirements, and the jacking pipe is directly above the close up penetration of the structural deformation of the operation tunnels is more influential.



(a) Line 9 underground tunnel



(b) Hang Hai Intercity Tunnel

Fig. 22. Additional radius of curvature of operational tunnels.

VI. Conclusion

The research successfully develops a risk assessment algorithm based on a combination of machine learning technology and pigeon-inspired optimization (PIO) algorithm to address the construction risks associated with urban railway tunnel projects. This PIO-BP neural network-based risk assessment model effectively identifies and assesses risks, leading to improved prediction accuracy. The study also provides a corresponding risk control scheme, which has been validated using monitoring data and numerical models, confirming the feasibility of the proposed risk assessment and control measures. The algorithm and approach provide a solid foundation for risk management in complex urban railway tunnel projects.

While acknowledging the contributions of this study, there are three key limitations that cannot be overlooked: Firstly，the risk identification process primarily relies on expert consultations and qualitative analysis, lacking quantitative automation support, which may impact the comprehensiveness and accuracy of risk identification. Then, while machine learning algorithms improve accuracy, the risk assessment indicator system could benefit from deeper quantitative analysis, leveraging big data technologies to enhance the granularity of risk predictions. Finally, the proposed risk assessment model is validated on specific projects but lacks clarity on its adaptability under different geological and environmental conditions, limiting its feasibility for broader applications.

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