Prediction model of surrounding rock deformation in double-continuous-arch tunnel based on the ABC-WNN

Yahui Zhang
Hebei Urban and Rural Construction School, Shijiazhuang, China

Received 26 June 2024
Revised 26 August 2024
12 September 2024
Accepted 18 September 2024

Abstract

Purpose – The wavelet neural network (WNN) has the drawbacks of slow convergence speed and easy falling into local optima in data prediction. Although the artificial bee colony (ABC) algorithm has strong global optimization ability and fast convergence speed, it also has the drawbacks of slow speed while finding the optimal solution and weak optimization ability in the later stage.

Design/methodology/approach – This article uses an ABC algorithm to optimize the WNN and establishes an ABC-WNN analysis model. Based on the example of the Jinan Yuhan underground tunnel project, the deformation of the surrounding rock of the double-arch tunnel crossing the fault fracture zone is predicted and analyzed, and the analysis results are compared with the actual detection amount.

Findings – The comparison results show that the predicted values of the ABC-WNN model have a high degree of fitting with the actual engineering data, with a maximum relative error of only 4.73%. On this basis, the results show that the statistical features of ABC-WNN are the lowest, with the errors at 0.566 and 0.573, compared with the single back propagation (BP) neural network model and WNN model. Therefore, it can be derived that the ABC-WNN model has higher prediction accuracy, better computational stability and faster convergence speed for deformation.

Originality/value – This article uses firstly the ABC-WNN for the deformation analysis of double-arch tunnels. This attempt laid the foundation for artificial intelligence prediction in deformation analysis of multi-arch tunnels and small clearance tunnels. It can provide a new and effective way for deformation prediction in similar projects.

Keywords Double arch tunnel, Deformation prediction, Artificial bee colonies, Surrounding rock, Wavelet neural network

Paper type Research paper

1. Introduction

The scientific analysis and processing of the deformation data generated by the urban double-connected arch tunnel in the construction and operation period and the use of a certain mathematical prediction model to make an accurate prediction of the deformation amount can effectively prevent the large deformation during the construction and operation of the tunnel, thus causing safety accidents. The deformation of the tunnel, especially the lining deformation caused by the construction of other buildings in the surrounding area, will be affected by many factors, which have the characteristics of complexity and variability, and the deformation data have non-linearity and pluralism, which makes it difficult to

This study was funded by the Natural Science Foundation of Hebei Province (No: E2020210068) and Project of Science and Technology Research and Development Program of China National Railway Group Co., Ltd. (No: N2020G009).

Railway Sciences
Vol. 3 No. 6, 2024
pp. 717-730
Emerald Publishing Limited
e-ISSN: 2755-0915
p-ISSN: 2755-0907
DOI 10.1108/RS-06-2024-0021

predict the deformation of the tunnel lining. Nowadays, in engineering practice, the deformation prediction of buildings mainly includes empirical method, regression analysis method, gray dynamic model (GM), artificial neural network, Kalman filter model, Fourier transform, (Jiang, Yan, Ouyang, Liu, & Zheng, 2023; Zhao, 2009; He, 2016; Jiang, Zhang, Gao, Xu, Pan, & Wang, 2020; Zhang, Zhang, Huang, Chen, & Zhao, 2021; Gong, Yang, Zhang, Luo, & Chen, 2022; Shen, Xiao, & Zhang, 2015), etc. However, using the traditional analysis method needs to establish a mature mechanical model and set the rock and soil mass parameters of each factor. In this way, it gradually deviates from the heterogeneous and anisotropic characteristics of rock and soil mass in the actual situation, and the prediction results are seriously biased. It is precisely because of these characteristics that artificial neural network models can better adapt to double-arch tunnels under multi-factor coupling and have strong solving ability for deformation of surrounding rock and middle partition wall.

In recent years, many scholars have put forward many kinds of combined prediction models on the basis of the existing algorithms and prediction models, which improve the accuracy of data prediction under complex engineering conditions year by year. Fan, Zhou, Xiong, and Zhao (2014) used the particle swarm algorithm to mature and produce oscillation phenomenon near the global optimal solution (Long, Jia, & Wan, 2013). On the basis of back-propagation (BP) neural network analysis, an analytic network process–back propagation (ANP-BP) model was proposed and compared with the optimized BP neural network, and it was found that the traditional BP neural network model was leaned slowly and prone to local minimum problems. Tan, Wei, and Hu (2015) used MATLAB programming to establish an improved BP neural network model, an auxiliary wavelet neural network (WNN) and an embedded WNN model, which achieved better prediction effects than the BP model. Zhao (2016) used the WNN analysis to predict the surface subsidence in tunnel construction and considered the influence of various external factors such as average surface pressure in the surface subsidence, which improved the realistic performance of the function and reduced the estimation error.

Zhu *et al.*, (2023) relied on the shield tunneling section of the Nanjing Metro Line 6 and used the artificial bee colony (ABC) algorithm to optimize the BP neural network. They established an ABC-BP neural network model that could predict surface settlement. The results of predicting surface settlement for three consecutive sections showed that the prediction accuracy and stability of the ABC-BP neural network were better than those of the BP neural network. Yu and Guo (2007) used WNN to model and predict the time series of network traffic data. In response to the shortcomings of traditional WNN training algorithms, they established a wavelet network prediction model, which was optimized based on the adaptive quantum-behaved particle swarm optimization (AQPSO) algorithm. The results showed that WNN had faster convergence speed and a more direct ability to approximate the optimal solution than BP neural networks. However, their disadvantage was that they could not achieve global search and could not guarantee the stability of predicted data. After optimization, they improved the shortcomings of traditional WNN and improved its prediction accuracy and stability. The ABC algorithm is easy to operate, has simple model parameter settings, fast convergence speed and high accuracy and, more importantly, can achieve global and local search in iterations.

Based on these characteristics, the article first uses the ABC algorithm to optimize the initial weights and thresholds of the WNN, constructs an ABC-WNN model to predict the actual engineering deformation and compares it with the actual monitoring quantity to analyze the prediction accuracy of this model. This optimization algorithm improves the accuracy of rock deformation prediction for double-arch tunnels and provides an effective prediction model and method for similar projects.

2. An optimized artificial bee colony wavelet neural network (ABC-WNN) algorithm

2.1 WNN algorithm

WNN is a new type of neural network that combines wavelet analysis and neural network. Its network structure is similar to the BP model, but the difference lies in the excitation functions of hidden layer neurons. BP neural network uses the Sigmoid function, while WNN uses the wavelet basis function. Numerous studies have shown that a nonlinear mapping problem can be approximated with arbitrary accuracy through a three-layer feedforward network (Wu, 2022). The structure of WNN is shown in Figure 1.

In Figure 1, Y represents the expected output value in the WNN, and its calculation formula can be represented by Equation (1):

$$Y = \sum_{n=1}^{L} W_n \Psi\left(\frac{x - b_n}{a_n}\right) \tag{1}$$

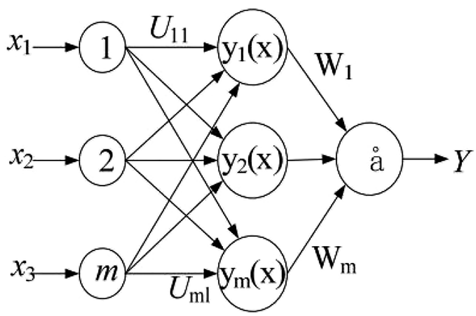
In the formula, W_n represents the expected value output by the n hidden layer node. At this point, if h_n represents the input value of the n hidden layer node, then

$$h_n = \sum_{m=1}^{t} U_{mn} X_m \tag{2}$$

In the formula, U_{mn} represents the weight between the n wavelet base unit and the m input value. Therefore, Formula (1) is transformed into Equation (3):

$$Y = \sum_{n=1}^{L} W_n \Psi\left(\frac{h_n = \sum_{m=1}^{t} U_{mn} X_m - b_n}{a_n}\right) \tag{3}$$

Assuming the sample data are $[[x_t, y_t]$ $(x_t \in R, y_t \in R\ ,\ t = 1, 2, \ldots, N)$, x_t and y_t in the data represent the input and output data of the WNN, respectively. They are trained based on the training data in the network using the gradient descent method. The parameters in Equation (3) are determined, and the error energy function is expressed in Equation (4):



Source(s): Author's own work

Figure 1. Structure of wavelet neural network

$$E = \frac{1}{2} \sum_{t=1}^{N} \left(y_{n} - \overline{y}_{n} \right) \tag{4}$$

In the formula, $\overline{y}_n$ is the network output data of the n input sample. The neural function of the hidden layer network uses the Morlet wavelet function for output:

$$\Psi(x) = \cos(cx) * e^{-\frac{x^2}{2}} \tag{5}$$

The network output data corresponding to the input x_t is:

$$\overline{y}_n = \sum_{n=1}^{L} W_n \Psi \left(\frac{\sum_{m=1}^{t} U_{mn} x_m - b_n}{a_n} \right) \tag{6}$$

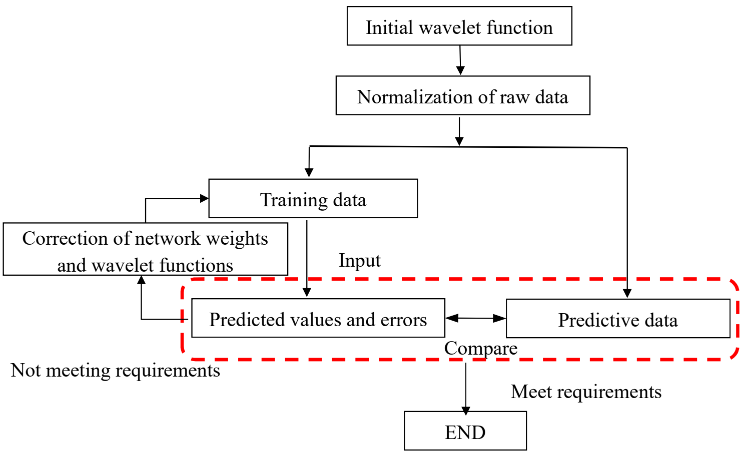
By substituting Equation (6) into Equation (4), the error energy function can be obtained:

$$E = \frac{1}{2} \sum_{t=1}^{N} \left[y_{n} - \sum_{n=1}^{L} W_n \Psi \left(\frac{\sum_{m=1}^{t} U_{mn} x_m - b_n}{a_n} \right) \right]^2 \tag{7}$$

The training steps of WNN algorithm are shown in Figure 2.

2.2 ABC algorithm

The ABC algorithm was proposed by Karaboga and Basturk *et al.* in the early 21st century to solve the problem of multi-variable function optimization. The algorithm is a bio-intelligent optimization algorithm that simulates bee colonies to search for excellent honey sources (Liang, 2014; Zhou, Hu, Wu, Zhong, & Wang, 2022; Liu & Wang, 2011; Wang, Xu, Li, & Feng, 2018).



Source(s): Author's own work

Figure 2.
Steps of wavelet neural network algorithm

In the ABC algorithm, bee colonies are divided into three parts: leading bees, following bees and scouting bees. The main task of leading bees is to search for food, making them the forefront of the bee colony. The main task of following bees is to wait for the leading bees to bring back food information, based on which they can determine and select available food sources. Leading bees rely on completely random information to search for food. When the food source for collecting bees is depleted or discarded by the leading bees, they will randomly search for new honey sources. The feasible solutions of the optimization problem correspond sequentially to the position of the nectar source, and the fitness function values correspond sequentially to the amount of nectar in the nectar source.

Firstly, the model randomly generates N initial values, such as x_i ($i = 1,2,\ldots,N$), which are vectors with a dimension of optimization parameter W. Each honey source attracts a leading bee, and N honey sources attract N leading bees and the corresponding position of N leading bees is the honey source location to be searched for. Leading bees and scouting bees will conduct a circular search. Unlike reconnaissance bees, the leading bee adopts a greedy criterion, which means that whenever the leading bee conducts a local search near the original flower honey source, it also searches for other new honey sources. If the amount of honey from the new honey source is greater than that from the old honey source, the leading bee will automatically replace the old one. After all leading bees complete the global search, they will share the honey source information with the following bees through tail-wagging dance. Once the honey source position has been locked, the following bee will conduct a local search around the honey source again along the search path, search for a new honey source and further determine the honey amount of that honey source. The probability of a leading bee with a large amount of nectar attracting a following bee is greater than that with a small amount of nectar. Once the amount of nectar obtained by the following bee from a new candidate honey source is greater than the determined old solution (i.e. the old honey source) on the search path, the model automatically replaces the old solution and completes the transition from old to new. On the contrary, the search results remain unchanged. The probability of following the bee to choose the honey source in the above non steps is obtained by the following Equation (8):

$$P = \frac{fit_i}{\sum_{n=1}^{N} fit_n} \tag{8}$$

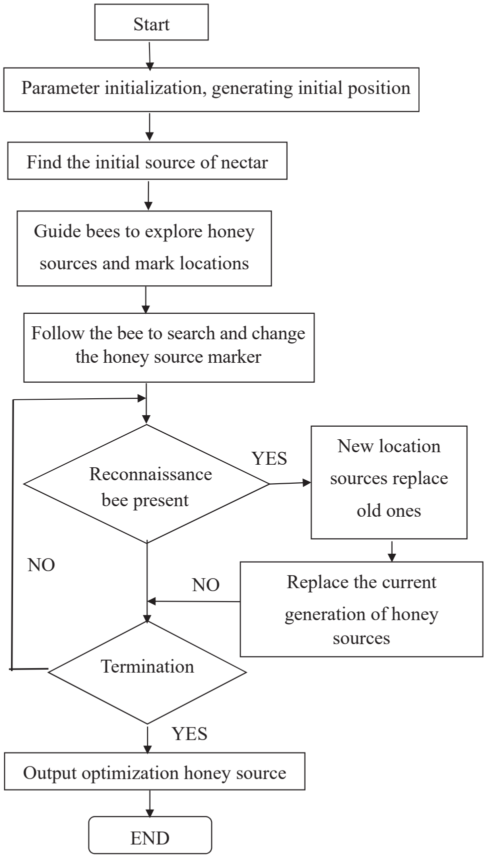
In the formula, fit_i is the fitness function value corresponding to the i solution.

In the ABC algorithm, Equation (9) is used to find a new candidate honey source location from the previous generation's honey source location:

$$new\_X_i^j = X_i^j + \mathrm{rand}(-1,1)\left(X_i^j - X_k^j\right) \tag{9}$$

In the formula, $i, k \in \{1,2,\ldots N\}, j \in \{1,2,\ldots W\}$ are randomly selected, and the step size of r and (−1,1) can be appropriately reduced as needed.

If the number of searches by the leading bee and the following bee exceeds the limit (a control parameter in the ABC algorithm) and no higher fitness honey source is found, the honey source will be abandoned, and both will be converted into reconnaissance bees. A new honey source will be randomly searched for replacement. It can be seen that with the iterative search of this algorithm, the gap between the three bee colonies in searching for nectar sources gradually narrows, and the search space between $new\_X_i^j$ and X_i^j calculation step size also decreases. This not only ensures the accuracy of the calculation but also helps to obtain the final optimal solution. The specific process steps of the ABC algorithm are shown in Figure 3.



Source(s): Author's own work

Figure 3.
Steps of artificial bee colony algorithm

In summary, it can be seen that the state of the following bee changes with the size of the leading bee's search for the optimal honey source, which ensures the maximization of the colony's interests, i.e. finding the optimal honey source. The reconnaissance bee always follows a small number of leading bees to randomly search for honey sources, ensuring the diversity of honey sources. This comprehensive and diverse search strategy helps to jump out of local optima and search for the optimal solution in the global context. Therefore, the ABC algorithm has strong adaptability and good universality, accelerates the convergence speed of the algorithm and reduces oscillations in the search process.

2.3 ABC-WNN algorithm

As mentioned earlier, a single WNN is prone to falling into local optima and has a slow convergence speed. Relatively speaking, the ABC algorithm converges quickly, but the accuracy cannot be improved due to the incomplete search of local information by the bee colony during solving; This article proposes an improved and optimized ABC-WNN prediction method, which improves the ABC algorithm and optimizes the initial weights and thresholds of WNN, so that all individuals in the bee colony can obtain corresponding function values through fitness function calculation and continuously search for the optimal fitness value and its corresponding individuals in search, eliminate the remaining non optimal solutions and finally use the training and learning of WNN to output the predicted value. This model not only reduces the uncertainty of parameter selection but also improves prediction accuracy and calculation speed while ensuring convergence speed.

3. Engineering case analysis

3.1 Project overview

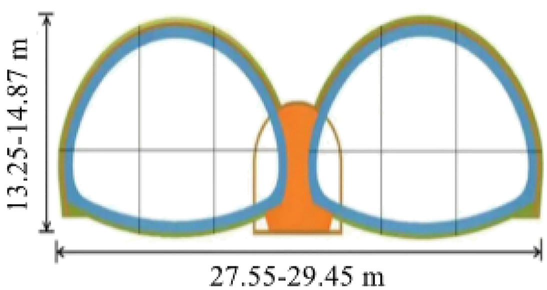
The experimental object selected in this article is the Jinan Yuhan Road underground tunnel project, which adopts a double arch tunnel structure. The starting and ending mileage of the tunnel excavation section is K15 + 305-K18 + 565, with a total length of 3.26 km. The tunnel is designed as a two-way six lane tunnel with an excavation section span of 27.55 m and an overlying strata thickness of 8–10 m. It belongs to a typical urban large-section double-arch shallow-buried tunnel, as shown in Figure 4.

According to the geological survey data of the construction of the Yuhan Road underground tunnel in Jinan, the geological strata of the site from top to bottom are mainly miscellaneous fill, silty clay, clay, residual soil, strongly weathered diorite and moderately weathered diorite. Groundwater of the tunnel mainly consists of quaternary pore water and bedrock fissure water.

3.2 Establishment of ABC-WNN model

The monitoring data of 30 days of arch crown settlement deformation and top displacement of the middle partition wall on the K16 + 415 and K17 + 550 sections of the Yuhan Road underground tunnel are selected as the basic data, and a model for analysis was established. Due to limited space, only the relevant data of the left tunnel within 30 days are listed. Specifically, Tables 1 and 2 provide a summary of the original data on the deformation of the surrounding rock and middle wall in sections K16 + 415 and K17 + 550, respectively. After multiple experiments and analyses, in the optimized ABC-WNN model, the initial population size is set to $N = 50$ (i.e. 50 initial solutions are randomly generated), with half of the leading and following bees, and the maximum number of iterations set to 800. The maximum number of cycles and termination cycles for ABC in searching for nectar sources are both set to 100. Divide the 30 monitoring data periods in Tables 1 and 2 into 2 parts: learning data and prediction data. The learning data are taken from the first 20 periods, and the prediction data are taken from the last 10 periods.

MATLAB 2020a was used to establish an ABC-WNN model and make predictions. The prediction results and relative errors are shown in Figures 5 and 6.



Source(s): Author’s own work

Figure 4. Section of the Jinan Yuhan Road underground tunnel

Table 1. Original deformation data of surrounding rock and middle partition wall (K16 + 415)

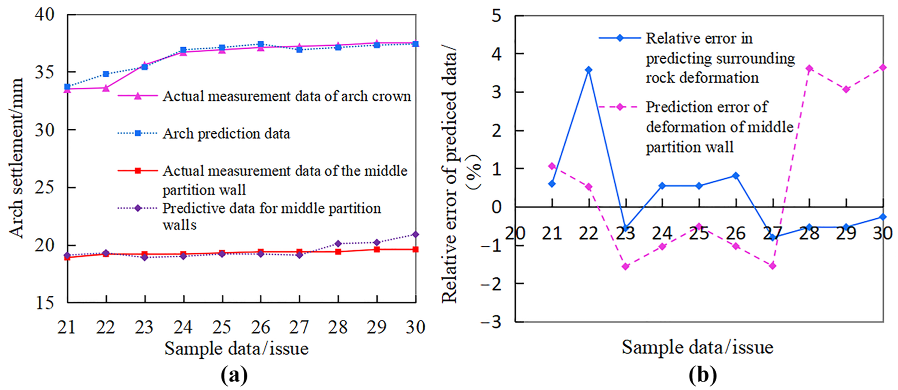
Order number	Deformation of surrounding rock	Deformation of middle partition wall	Order number	Deformation of surrounding rock	Deformation of middle partition wall	Order number	Deformation of surrounding rock	Deformation of middle partition wall
1	23.7	7.8	11	29.9	12.9	21	33.5	18.9
2	24.2	8.2	12	30.4	13.4	22	33.6	19.2
3	25.5	8.5	13	30.6	14.6	23	35.6	19.2
4	25.3	8.6	14	30.9	14.9	24	36.7	19.2
5	26.1	9.4	15	30.9	15.1	25	36.9	19.3
6	26.8	9.8	16	31.6	15.3	26	37.1	19.4
7	27.5	11.2	17	31.9	16.7	27	37.2	19.4
8	28.0	11.6	18	32.2	16.8	28	37.3	19.4
9	28.5	11.9	19	32.5	18.1	29	37.5	19.4
10	29.6	12.8	20	32.9	18.5	30	37.5	19.4

Note(s): Unit: mm
Source(s): Author's own work

Table 2. Original deformation data of surrounding rock and middle partition wall (K17 + 550)

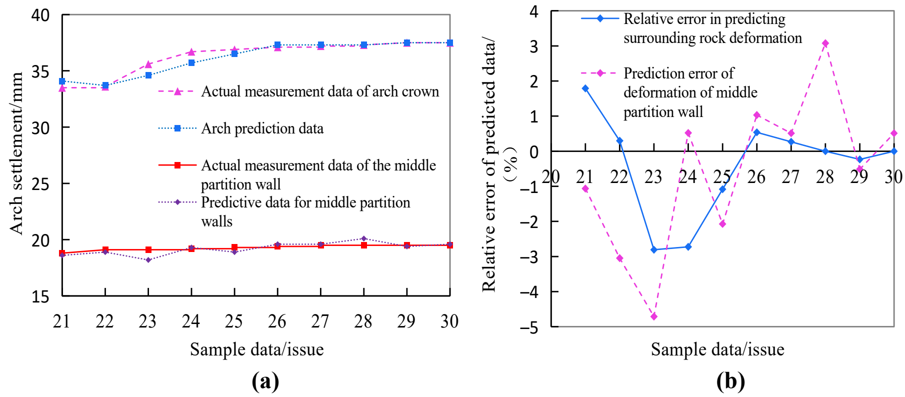
Order number	Deformation of surrounding rock	Deformation of middle partition wall	Order number	Deformation of surrounding rock	Deformation of middle partition wall	Order number	Deformation of surrounding rock	Deformation of middle partition wall
1	22.5	7.7	11	29.8	12.7	21	34.1	18.5
2	24.1	8.2	12	30.2	13.4	22	33.7	19.1
3	25.6	8.4	13	30.4	14.6	23	34.6	19.1
4	25.7	8.7	14	30.7	14.9	24	35.7	19.2
5	26.2	9.2	15	30.9	15.2	25	36.5	19.3
6	26.8	9.6	16	31.5	15.3	26	37.3	19.3
7	27.5	10.2	17	32.3	16.8	27	37.3	19.5
8	28.2	11.4	18	32.5	16.9	28	37.3	19.5
9	28.4	11.7	19	32.5	17.8	29	37.5	19.5
10	29.1	12.2	20	32.9	18.2	30	37.5	19.5

Note(s): Unit:mm
Source(s): Author's own work



Source(s): Author's own work

Figure 5.
Comparison of deformation prediction results and measured data for K16 + 415 section



Source(s): Author's own work

Figure 6.
Comparison of deformation prediction results and measured data for K17 + 550 section

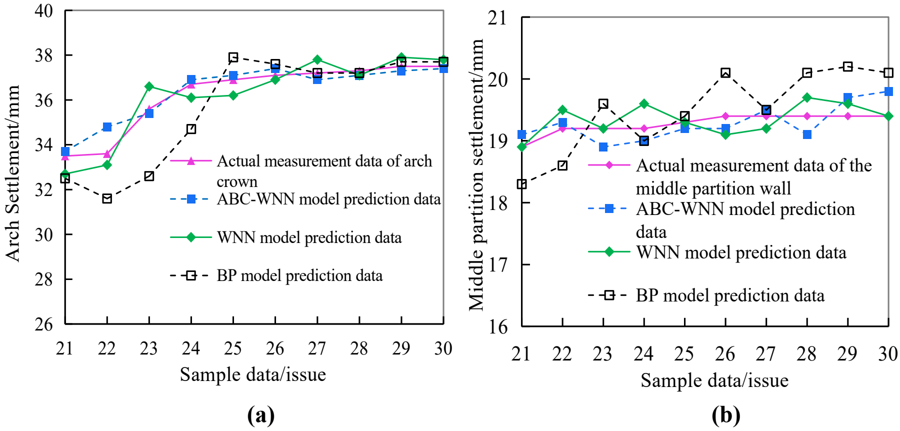
From Figures 5 and 6, it can be seen that the ABC-WNN model has a high degree of fitting between the predicted values and actual engineering data, with a maximum relative error of only 4.73%, indicating that the predictive function of the model is relatively reliable.

3.3 Prediction results and accuracy testing

3.3.1 Comparison of relative errors. This section analyzes data based on the ABC-WNN model and compares the results of deformation prediction analysis for the same section using a single WNN prediction model and a BP neural network prediction model to determine whether the optimized WNN model has higher and more effective prediction performance. Among them, according to Yang and Wang (2022), when the optimal number of hidden layer nodes is set to 10 in the BP model, the operational error is minimized. Therefore, in this section, the training accuracy of the BP model is set to 0.001, and the number of learning and training sessions is set to 1,500. The scaling and translation parameters of WNN model are randomly selected in [−1,1].

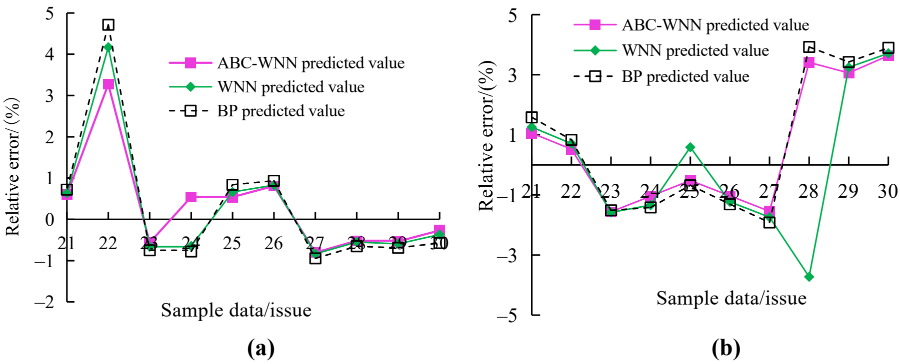
Taking K16 + 415 segment as an example, three models were initialized, learned, trained and predicted. The comparison results between the predicted results and relative errors are shown in Figures 7 and 8.

From Figures 7 and 8, it can be seen that the prediction results of WNN, BP and ABC-WNN are relatively close to the measured data, and the relative errors are also relatively small. Among them, ABC-WNN has the best prediction effect and the smallest prediction



Source(s): Author's own work

Figure 7. Comparison of deformation prediction results of different calculation models for K16 + 415 section



Source(s): Author's own work

Figure 8. Comparison of relative errors in deformation prediction of different calculation models for K16 + 415 section

Index	BP	WNN	ABC-WNN
MAE	0.815	0.788	0.573
MSE	1.434	1.427	0.566

Source(s): Author's own work

Table 3. Comparison of prediction errors among three models

error, followed by WNN. The BP model has the largest relative error, indicating that the ABC-WNN algorithm has the highest degree of fitting and can play the most predictive role.

3.3.2 Comparison of mean square and mean absolute error. In statistics, the commonly used indicators to measure the accuracy of data fitting are mean absolute error (MAE) and mean squared error (MSE) (Li, Zhao, Xu, Wang, & Yang, 2022; Asteris *et al.*, 2021). MAE is an analytical method used to measure the absolute error between predicted values and true values, which can be calculated using Equation (10), while MSE is a statistical measure that measures the degree of model fit based on the square difference. It can more accurately reflect the degree of deviation of predicted value errors, which can be calculated using Equation (11).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\overline{y_i} - y_i\right| \tag{10}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\overline{y_i} - y_i\right)^2 \tag{11}$$

In order to further evaluate the final fitting accuracy of BP, WNN and ABC-WNN, MAE and MSE are selected to examine the predictive performance of each model in this section. The comparison results are shown in Table 3.

From Table 3, it can be seen that the MSE of the optimized ABC-WNN algorithm is only 0.566, while the MSE of the other two models is 2.53 times and 2.52 times that of ABC-WNN, respectively. The average absolute error reaches 1.42 times and 1.37 times that of ABC-WNN, respectively.

Therefore, whether from a relative error or statistical perspective, the ABC-WNN model has higher accuracy and stability in predicting performance.

4. Conclusion and prospect

By simulating and predicting the deformation of the surrounding rock and the deformation of the middle partition wall of the underground double-arch tunnel on the Yuhan Road in Jinan, it can be seen that:

In terms of comparison with measured values, the predicted values of the optimized ABC-WNN have a high degree of fitting with actual engineering data, with a maximum relative error of only 4.73%, indicating that the predictive function of the model is relatively reliable.

In terms of comparing the prediction results with other models, the optimized ABC-WNN has the smallest MSE in prediction accuracy, while the MSE of BP and WNN are 2.53 and 2.52 times that of the former, respectively. In terms of average absolute error, ABC-WNN still has the lowest, while the average absolute errors of BP and WNN are 1.42 and 1.37 times that of the former, respectively. This indicates that the prediction results of optimized ABC-WNN are more stable, providing a new and effective prediction approach for similar projects.

Regarding the limitations and future work, although the ABC-WNN model used in this article has optimized, it has ignored the deformation effects that have already occurred during the early construction, as well as the insufficient consideration of settlement and convergence caused by other dynamic effects. Therefore, the deformation mechanism of the tunnel itself will be further considered to improve the authenticity of data fitting and prediction accuracy.

References

Asteris, P. G., Koopialipoor, M., Armaghani, D. J., Kotsonis, E. A., & Lourenco, P. B. (2021). Prediction of cement-based mortars compressive strength using machine learning techniques. *Neural Computing and Applications*, *33*(19), 13089–13121. doi: 10.1007/s00521-021-06004-8.

Fan, S., Zhou, Q., Xiong, X., & Zhao, J. (2014). Tunnel deformation prediction model based on support vector machinewith particle swarm optimization algorithm. *Computer Engineering and Applications*, *50*(5), 6–10.

Gong, S., Yang, Z., Zhang, G., Luo, X., & Chen, X. (2022). Study on tunnel geotechnical physical parameters analysis method based on optimized BP neural network algorithm. *Northwest Hydropower*, *5*, 133–137.

He, L. (2016). Research on new support form and excavation methods for large-section small spacing tunnel in loess. PhD thesis. Beijing: Beijing Jiaotong University.

Jiang, J., Zhang, Z., Gao, M., Xu, L., Pan, J., & Wang, X. (2020). An abnormal crowd behavior detection method based on streak flow CNN. *Advanced Engineering Sciences*, *52*(6), 215–222.

Jiang, W., Yan, J., Ouyang, Y., Liu, L., & Zheng, H. (2023). Calibration of micro parameters of particles in granular discrete element method to assess slope stability by strength reduction method. *Advanced Engineering Sciences*, *55*(5), 1–14.

Li, X., Zhao, M., Xu, C., Wang, W., & Yang, J. (2022). Detecting looseness of bolts of high-speed trains based on nonlinear lamb wave. *High speed Railway Technology*, *13*(5), 31–35. doi: 10.3390/bs13010031.

Liang, Y. (2014). The study of artificial bee colony algorithm for high dimensional optimization based on mutual learning. MA thesis. Dalian: Dalian University of Technology.

Liu, L., & Wang, T. (2011). Support vector machine optimization based on artificial bee colony algorithm. *Journal of Tianjin University*, *44*(9), 803–809.

Long, X., Jia, N., & Wan, J. (2013). On metro tunnel settlement prediction by ANP-BP based models. *Modern Tunnelling Technology*, *50*(5), 105–111.

Shen, S., Xiao, L., & Zhang, H. (2015). A forecasting method based on Fourier time series for short-term settlements in adjacent structures during an under-passing shield tunnel construction. *Journal of Fuzhou University (Natural Science Edition)*, *43*(2), 238–244.

Tan, Q., Wei, J., & Hu, J. (2015). Building deformation prediction based on wavelet analysis and BP neural network. *Journal of Basic Science and Engineering*, *23*(3), 629–636.

Wang, R., Xu, H., Li, B., & Feng, Y. (2018). Research on method of determining hidden layer nodes in BP neural network. *Computer Technology and Development*, *28*(4), 31–35.

Wu, C. (2022). Design of tunnel settlement prediction method based on artificial bee colony algorithm. *Adhesion*, *49*(11), 136–139.

Yang, F., & Wang, Y. (2022). Study on combination forecast of railway passenger volume by improved particle swarm optimization algorithm based on natural selection. *High Speed Railway Technology*, *13*(6), 63–68.

Yu, J., & Guo, P. (2007). Study on network traffic forecast based on improved wavelet neural network. *Journal of Computer Applications*, *27*(12), 2986–2990.

Zhang, Z., Huang, X., Chen, H., & Zhao, C. (2021). Prediction of tunnel settlement based on grey LSTM neural network combined model. *Journal of Hebei University of Engineering (Natural Science Edition)*, *38*(4), 53–59.

Zhao, X. (2009). Study on stability of the medium partition in double-arch tunnel. MA thesis. Xi'an: Xi'an University of Science and Technology.

Zhao, F. (2016). Application of wavelet neural network in the monitoring of tunnel settlement. *Science Surveying and Mapping*, *41*(12), 283–287.

Zhou, X., Hu, J., Wu, Y., Zhong, M., & Wang, M. (2022). A multi-strategy artificial bee colony algorithm based on fitness grouping. *Pattern Recognition and Artificial Intelligence*, *35*(8), 688–700.

Zhu, C., Wang, Z., Long, F., Li, F., Feng, T., & Zhang, J. (2023). Prediction of ground settlement of subway shield based on ABC-BP neural network. *Journal of Hohai University (Natural Sciences)*, *51*(4), 72–80.

Corresponding author
Yahui Zhang can be contacted at: zhangyahui19891020@163.com