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Ground Surface Settlement Prediction of Rectangular Pipe Jacking Tunnels Based on the Improved PSO-BP Neural Network Algorithm

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Abstract

In the construction of rectangular pipe jacking tunnel projects, existing methods such as finite element and numerical simulation have difficulties in accurately predicting ground surface settlement caused by tunnel jacking. Therefore, this paper proposes a prediction model for ground surface settlement of shallow-buried large-section rectangular pipe jacking tunnels based on the Back-Propagation (BP) neural network. Considering the high approximation ability of BP neural networks for arbitrary functions under multi-parameter inputs, an adaptive mutation method is introduced. The Particle Swarm Optimization (PSO) algorithm, improved with adaptive inertia weight and mutation particles for late-stage optimization, is employed to determine the optimal hyperparameters of the prediction model. A PSO-BP prediction model for ground surface settlement of shallow-buried large-section rectangular pipe jacking tunnels is established. A case study of a shallow-buried large-section rectangular pipe jacking tunnel is conducted. The proposed algorithm is compared and analyzed with traditional algorithms in conjunction with field monitoring data. The prediction results show that the improved PSO-BP neural network prediction model exhibits more stable prediction performance than the traditional BP neural network prediction model, both in cases of gentle and significant concave-convex changes in ground surface settlement. The predicted settlement values are closer to the actual values, and the prediction accuracy and robustness are significantly enhanced.

Keywords

BP neural network, ground surface settlement, tunnel construction, rectangular pipe jacking, particle swarm optimization.

1. Introduction

Rectangular pipe jacking technology is widely used in urban underpass tunnel projects due to its construction safety and minimal disturbance to the surrounding environment. During the jacking process of shallow-buried large-section rectangular pipe jacking tunnels, inevitable disturbances are introduced to the surrounding strata, altering the distribution of the stress and displacement fields. Over time, these disturbances ultimately influence the overall consolidation settlement of the strata where the tunnel is located. Therefore, accurately predicting ground surface settlement induced by rectangular pipe jacking tunnels is of great significance in reducing the impact of construction on the surrounding environment and ensuring the safety of the project.

Artificial intelligence algorithms possess robust information processing capabilities, such as nonlinearity, high parallelism, and high fault tolerance in learning and generalization abilities[1]. Among these, machine learning algorithms can learn data features through a sufficient number of sample inputs, and then perform regression fitting analysis to effectively analyze new inputs with similar patterns and make predictions[2]. In recent years, artificial neural networks, support vector machines, and random forests have become the primary machine learning algorithms used to predict ground surface settlement caused by shield tunneling[3]. Ramezanshirazi and Tang[4][5] et al. have both employed machine learning algorithms to effectively predict ground surface settlement induced by tunnel construction. Chen[6] et al. compared the efficiency and feasibility of six machine learning algorithms and found that regression neural networks and random forests exhibited the best performance among them, accurately identifying the evolution of settlement caused by tunneling. Elbaz[7] et al. proposed a computational model combining improved Particle Swarm Optimization (PSO) with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the performance of Earth Pressure Balance (EPB) shield tunneling. Cao[8] et al. developed a deep learning model that offers higher prediction accuracy and acceptable computational efficiency compared to existing machine learning techniques and algorithms. Li et al.[9] effectively predicted the settlement development in different strata caused by large-diameter shield tunneling using the Long Short-Term Memory (LSTM) machine learning algorithm. Ghiasi et al.[10] designed a Multilayer Perceptron (MLP) artificial neural network to accurately predict ground surface settlement after individually assessing a series of variables influencing settlement, such as soil cohesion, internal friction angle, and permeability coefficient. As research progresses, machine learning algorithms are expected to be increasingly utilized in tunnel engineering.

This study relies on the real-time monitoring data from the rectangular pipe jacking tunnel construction of the West Extension Line of Liuye Avenue to establish a ground surface settlement prediction model for rectangular pipe jacking tunnels using an improved Particle Swarm Optimization (PSO) algorithm combined with the traditional BP neural network, namely the PSO-BP model. The prediction performance and stability of the new and traditional algorithms are compared and analyzed to provide theoretical support and technical references for the design and construction of similar rectangular pipe jacking tunnels.

2. Settlement Prediction Methods

2.1. The PSO-BP Algorithm

The improved PSO-BP neural network model proposed in this study is hereinafter referred to as the PSO-BP model. The traditional BP neural network is renowned for its strong nonlinear mapping capability and flexible network architecture. The number of hidden layers and the number of neurons in each layer can be arbitrarily determined based on specific conditions, rendering the operation relatively simple and convenient. However, it suffers from a slow learning rate and prolonged convergence time, leading to suboptimal performance. Moreover, the initial weights and thresholds, which are randomly generated, can significantly influence the results, thereby substantially reducing the overall prediction accuracy of the network. To mitigate these effects, this study employs an improved Particle Swarm Optimization (PSO) algorithm, which incorporates a linearly decreasing inertia weight ω^i incorporating a linearly decreasing inertia weight to better balance the global and local search capabilities of the algorithm. The update formula is shown in Equation (1).Through global particle search, when particles become trapped in local optima during later stages, mutation is introduced to escape the local points and resume the search process. This iterative procedure continues until the optimal individual and the target loss value are identified, followed by fitness evaluation based on the fitness function *Fitness* as defined in Equation (2). Otherwise, the iteration proceeds further. This mechanism optimizes the adjustment of weights and thresholds, thereby accelerating the convergence speed of the network and enhancing its learning efficiency.

$$\omega^{i} = \omega_{start} - (\omega_{start} - \omega_{end}) \times \left({}^{i}/_{i_{all}}\right) \tag{1}$$

$$Fitness = \sum_{i=1}^{n} (x_i - y_i) \tag{2}$$

In the formula: are the initial and final inertia weights; are the current and total number of iterations; are the predicted and actual values of the output layer.

2.2. Data Processing and Model Evaluation

To prevent gradient explosion during network training caused by varying scales of different indicators, the input data should undergo preprocessing and normalization before being fed into the network. As shown in Equation (3), the normalization operation maps all data to the interval [-1, 1]. Upon completion of all computations, inverse normalization is applied, followed by result visualization.

$$x_m = 2 \times \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{3}$$

In the formula:x_{min}、 x_{max} represents the maximum value of the data x.

To evaluate the performance differences between the two algorithms in predicting ground settlement induced by rectangular pipe jacking tunneling, this study employs three error metrics: the correlation coefficient (R), mean squared error (MSE), and mean absolute error (MAE) to assess model superiority.

2.3. Database

All data in this study were obtained from field monitoring at the Liuye Avenue rectangular pipe-jacking tunnel construction site. According to the research by Zhang et al.[11], the factors influencing surface settlement can be categorized into four groups: tunnel geometric parameters, driving parameters, geological conditions, and anomalous factors.

Given that manual excavation was carried out simultaneously at the same horizontal level, the tunnel specifications and burial depth remained virtually unchanged. Therefore, the influence of tunnel geometric parameters on the results is not considered in this study. In the selection of jacking parameters, the primary factors chosen were the jacking force and jacking speed. These parameters are key indicators for controlling pipe jacking construction and can be accurately and reliably collected in real-time through data acquisition systems such as sensors. Considering the significant impact of grouting pressure on over-excavation voids and subsequent settlement[12], the selected jacking parameters, including jacking force and jacking speed, are key indicators for controlling pipe jacking construction. These parameters can be accurately and reliably collected in real-time through data acquisition systems such as sensors. Geological conditions need to consider the basic physical and mechanical properties of soil layers, as well as the spatial location of the soil layers. The soil excavated in this project is relatively uniform, being silty clay throughout, and thus the influence of geological conditions on the results can be neglected. Since the tunnel jacking construction adopts manual excavation, the process is relatively simple with fewer abnormal factors, and thus is not considered in this study. In summary, the jacking force, jacking speed, and grouting pressure were selected as the input parameters for the prediction model. A total of 27 datasets were used, with the first 20 datasets (approximately 75%) employed for model training and the remaining 7 datasets used for testing and prediction.

3. Engineering Case Study

3.1. Project Profile

At chainage K7+081.113 along the road centerline of the Liuye Avenue West Extension Line, twin-cell rectangular pipe-jacking tunnels with a clear span of 18.2×6.0 m are installed. These tunnels intersect the Chang-Zhang Expressway at an angle of 63.881°. Each tunnel has a total length of 51 m, with an overburden thickness ranging from 2.000 to 2.683 m. Three intermediate jacking stations were installed for the construction of the rectangular pipe-jacking tunnels. The tunnels were prefabricated in four sections, with lengths of 12 m, 13 m, 13 m, and 13 m, respectively. The structural design utilized P8-grade C40 waterproof reinforced concrete. The roof and side walls of the rectangular pipe-jacking tunnels are 130 cm thick, while the base slab is 140 cm thick. The spacing between the two tunnels is 150 cm. The construction of the rectangular pipe-jacking tunnels involved the setup of working pits, reaction walls, slip planes, and on- site assembly of steel shield support frameworks. An innovative construction technique characterized by "oblique intersection, oblique construction, and axial jacking" was employed. A 4-cm-wide settlement joint was installed between each precast segment of the tunnels. The overall layout of the rectangular pipe-jacking tunnels on the Liuye Avenue West Extension Line is shown in Fig. 1 (elevations are in meters, and widths are in centimeters).

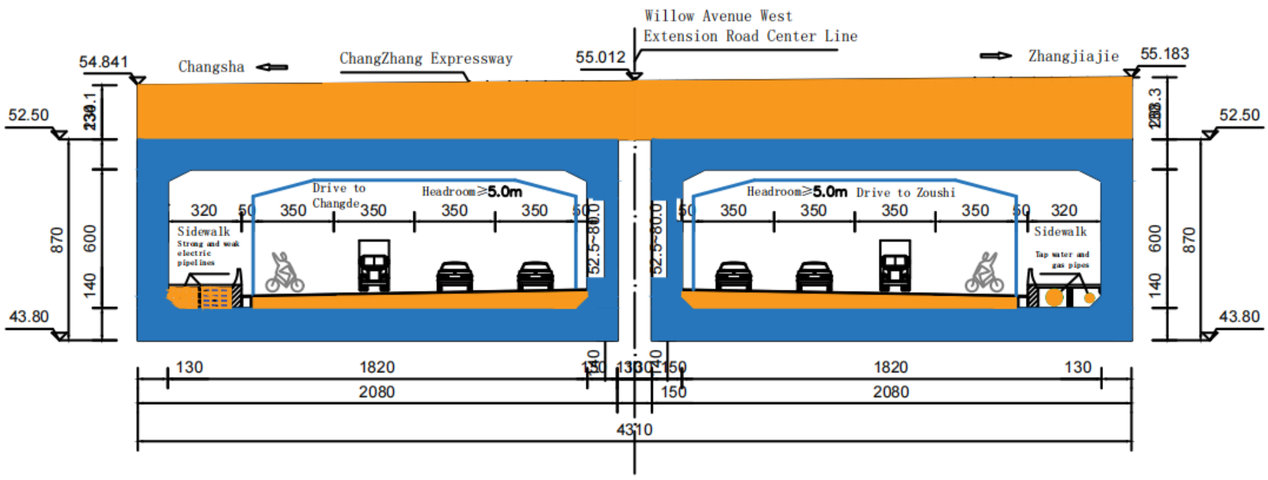

Fig. 1 Cross section of rectangular pipe jacking

3.2. Construction Methodology

During construction, traffic on the Chang-Zhang Expressway could not be interrupted. To address this challenge, a rigid shield support system was assembled on-site, and matching hydraulic jacks were strategically positioned at the intermediate jacking stations and the tail end of the rectangular pipe-jacking tunnel to facilitate the jacking process. However, the jacking operation inevitably disturbs the subgrade, causing settlement. Excessive settlement can compromise traffic safety. In this project, a rigid shield support system was employed to maintain the slope ratio of the highway, thereby enhancing the safety and applicability of the construction process. This approach is particularly reliable for frame jacking construction and effectively minimizes the disturbance to the highway subgrade during the jacking process under shallow cover conditions. Therefore, it is necessary to monitor the pavement deformation to control the jacking rate and excavation volume, thereby controlling settlement and ensuring both traffic safety on the highway and the safe emergence of the rectangular pipe-jacking tunnel.

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4. Prediction Results

4.1. Settlement Data Analysis

Based on the data and parameters mentioned above, two network models were established. When analyzing the longitudinal settlement data for a specific day, the four aforementioned variables were treated as constants, with the sole independent variable being the distance from the centerline of the rectangular pipe-jacking tunnel. Data were obtained based on the distribution of monitoring points. Longitudinal settlement was predicted using the method described above, and the comparison between the actual and predicted settlements for the left and right sections is shown in Fig. 2 and Fig. 3.

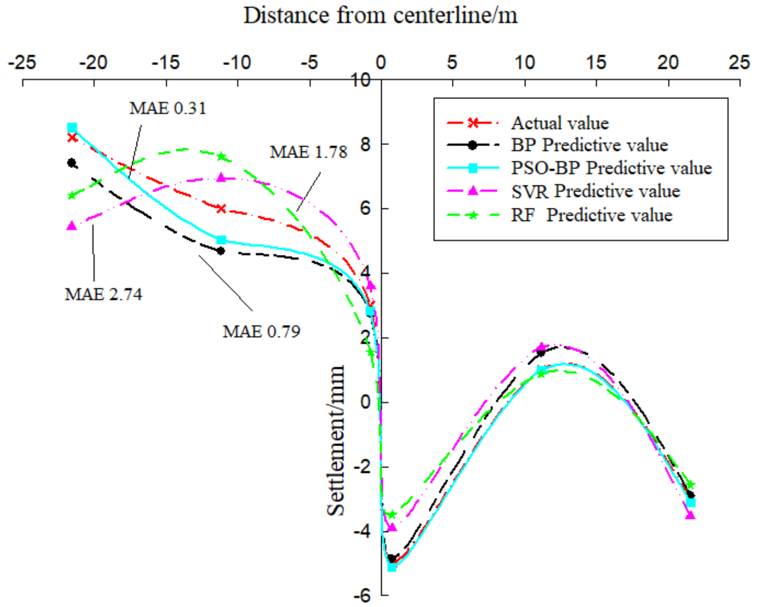

Fig. 2 Longitudinal measuring points on the left

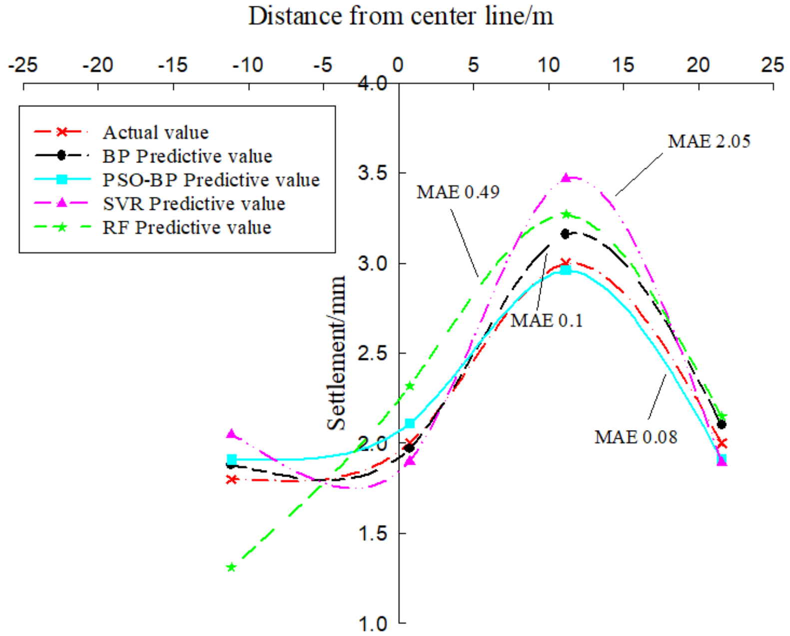

Fig. 3 Longitudinal measuring points on the right

As shown in Fig. 2 and Fig. 3, the traditional BP neural network exhibits significantly poorer prediction performance when the settlement values fluctuate greatly, and only performs adequately when the fluctuations are relatively mild. In contrast, the self-adaptive PSO-BP model, with a few exceptions where data distortion leads to poor predictions, generally achieves prediction results that are largely consistent with the actual settlement values. Overall, the PSO-BP model outperforms the traditional BP neural network model. It can be concluded that all four algorithm models demonstrate satisfactory prediction performance for longitudinal settlement data. However, while the SVM and RF models have higher error metrics compared to the BP neural network, the differences are not significant. In contrast, the improved PSO-BP algorithm exhibits lower error metrics and is more stable and superior.

4.2. Algorithm Performance Comparison

To better compare the prediction performance of the two algorithm models for the monitoring points on both sides of the rectangular pipe-jacking tunnels, the mean values of the evaluation indicators for the transverse monitoring points on both sides were primarily used for comparison. The comparison of prediction performance is shown in the figures below.Except for the explosion of the *MSE* metric in the BP model for the right-side rectangular pipe-jacking tunnel test set, all other *MSE* values were below 20. Moreover, the PSO-BP algorithm exhibited a significantly steeper decline in error compared to the unimproved algorithm. The maximum *MAE* for the PSO-BP algorithm was 1.72, while the maximum *MAE* for the unimproved algorithm was 5.79, resulting in a difference of 4.02. The minimum *MAE* for the PSO-BP algorithm was 0.96, compared to 1.57 for the unimproved algorithm, with a difference of 0.61. The differences in the minimum MAE values are relatively small, indicating that while the PSO-BP algorithm significantly outperforms the unimproved algorithm in terms of maximum error, the improvement in minimum error is less pronounced. The *R* values of the PSO-BP algorithm are significantly higher than those of the unimproved algorithm. The former remains above 0.90, while the latter reaches a maximum of 0.74. This comprehensively indicates that in the tunnel settlement prediction example of the excavation project presented in this paper, the PSO-BP algorithm has a deeper learning capacity and stability compared to the traditional BP neural network. It converges faster, has a more pronounced optimization effect, and requires relatively less time.

5. Conclusion

This study proposes an improved PSO-BP algorithm, which introduces an adaptive inertia weight and particle mutation factors. Combined with traditional BP, SVM, and RF models, the neural network is used to predict ground surface settlement. The main conclusions are as follows:

In the prediction of ground surface settlement caused by rectangular pipe jacking tunnel construction, the improved algorithm exhibited significantly lower errors compared to traditional BP, SVM, and RF models. The maximum single-point prediction error for the improved algorithm was -2 mm, while that for the traditional models was 30 mm. The mean overall prediction errors were -1.814 mm for the improved algorithm and 9.189 mm for the traditional models. Results in the longitudinal direction indicate that the improved algorithm outperforms the traditional algorithms, although the difference is not substantial.

When the settlement data exhibit large fluctuations, the error metrics of traditional neural networks tend to explode, failing to effectively capture the relationships between variables. In contrast, the improved algorithm demonstrates superior performance in fitting the true data.

Considering both prediction error and model performance, the improved PSO-BP model can serve as a reliable tool for predicting ground surface settlement caused by rectangular pipe-jacking tunnel construction.

It should be noted that the data in this study are limited to a specific tunnel construction project and do not account for other potential factors that may influence settlement. Therefore, further validation and adjustment of the model are necessary when applying it to other regions.

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