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Analysis of Surface Settlement in Large Section Tunnel Based on Improved BP Neural Network

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Abstract: In order to meet the growing demand for underground space for economic development and infrastructure needs, there are more and more underground space constructions represented by subways in various regions. Most of the subway tunnel projects cross the fault fracture zone with low quality, and the terrain conditions are extremely complex. In response to the special geological surface settlement problem of Qingdao Metro, this article takes the construction stage of the Chaobuling platform of Metro Line 4 as an example. Based on on-site monitoring and measurement data, combined with the initial weights of the BP neural network modified by the finite element analysis software MIDAS, displacement inversion analysis is carried out on the surface settlement data of the large cross-section tunnel. The model fitting results are checked using the post check difference test method, A BP neural network model with good fitting and generalization ability was obtained. This model optimizes the shortcomings of the BP neural network model, such as slow convergence speed and easy trapping in local minima, while also avoiding the drawbacks of large errors, inaccurate accuracy, and ground reliability in numerical simulation. The application of this method is suitable for solving large-scale and complex nonlinear tunnel engineering problems. Its stability and applicability are good, and its accuracy is greatly improved compared to traditional simulation methods, which has a guiding role for corresponding engineering.

1. Introduction

As large-scale underground space development in cities continues to boom, shallow sea collapse disasters remain one of the most challenging problems in tunnel engineering. In recent years, over 60 countries and regions worldwide have been involved in the construction of subway tunnels, and surface settlement severely affects both the safety of tunnel construction and the healthy development of urban rail transit [1-3]. The excavation disturbance and soil unloading during the tunnel construction stage are the main factors affecting surface settlement [4-5]. In this study, MIDAS numerical simulation and BP neural network were used to analyze the surface settlement caused by the excavation of the Cuobuling subway tunnel [6-11]. The impact of soil unloading on surface settlement was treated as a black-box system and identified using neural networks. After repeated training, the analysis and prediction of surface settlement in the unexcavated area were achieved. However, the BP neural network has inherent disadvantages such as slow convergence speed and a tendency to get stuck in local minima during prediction [12-13]. Therefore, numerical simulation was used to optimize the initial weight of the BP neural network, and a tunnel construction ahead-of-settlement prediction model based on MIDAS-BP neural network was established. The operational effectiveness of the BP neural network model was optimized, and the model fitting results were verified using the posterior difference check method based on measured data. Finally, the model was applied to predict the settlement in the unexcavated section during the construction stage.

2. Engineering Description

2.1. Project Overview

Cuobuling subway station is the ninth station of the Qingdao subway line 4, with a total length of 225m and an effective station center mileage of YCK8+883.000 (starting mileage YCK8+790.275 and ending mileage YCK9+016.775). The effective station platform is 118m long, with a total construction area of 16,335.4 ㎡. The station was constructed using the double-side-wall guiding pit cover excavation method, with two underground 13m island platforms and a calculated rail top absolute elevation of -1.00m at the station centerline. The station connects with the Qingdao subway line 3, with the main structure of line 3 above line 4, connected via the hall-to-hall transfer passage and platform-to-platform transfer passage. The station has two entrances (Entrance A and B) and three wind pavilion groups (Wind Pavilion Groups 1, 2, and 3, with Wind Pavilion Group 3 serving the interval). The station location map and station model are shown in Figures 1 respectively.

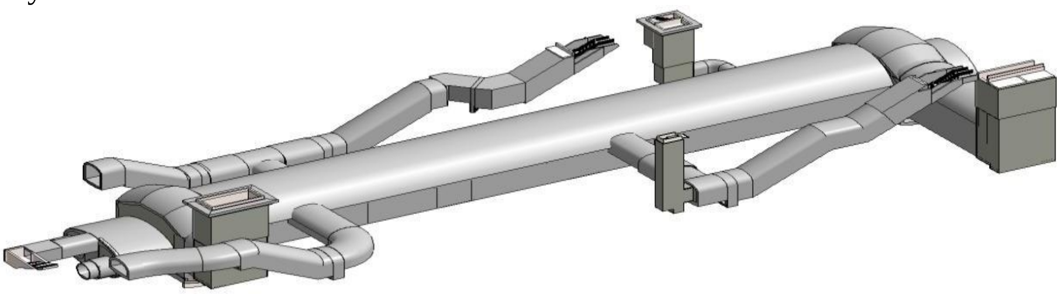

Figure 1: BIM model of cuobuling station platform

2.2. Geological Conditions

The construction site is primarily composed of three geological layers from top to bottom: artificial fill layer (Q_{4ml}), Holocene alluvial layer, and bedrock layer. The artificial fill layer (Q_{4ml}) mainly consists of backfilled cohesive soil, coarse sand, granite debris, and construction waste. The Holocene alluvial layer (Q_{4al+pl}) mainly consists of silty clay, quartz, and feldspar. The bedrock layer is mainly composed of late Yanshanian granite, with intercalated diorite, granodiorite, and tectonic rocks, and locally exposed fractured rocks. The main part of the Cuobuling Station is located in the bedrock layer, and the tunnel cross-section and soil parameters are shown in Figure 2.

According to the detailed exploration drilling results, the site is regularly distributed with dynamic metamorphic rock zones, structural fracture zones, and fill-type structures (vein rocks), with the dynamic metamorphic rock mainly consisting of fractured rocks. The main part of the station tunnel is located in the erosion accumulation first-level terrace geomorphic unit, all of which are located in the bedrock layer, with surrounding rock mainly consisting of III and IV grade surrounding rock, with intercalated structural fracture zones and fill-type structures (vein rocks) with V-grade surrounding rock. There are two vertical shafts on either side of the station, which pass through the Holocene alluvial layer and artificial fill layer to the ground surface from the bedrock layer. The surrounding rock grade around the shafts gradually decreases from bottom to top, mainly consisting of V-grade surrounding rock.

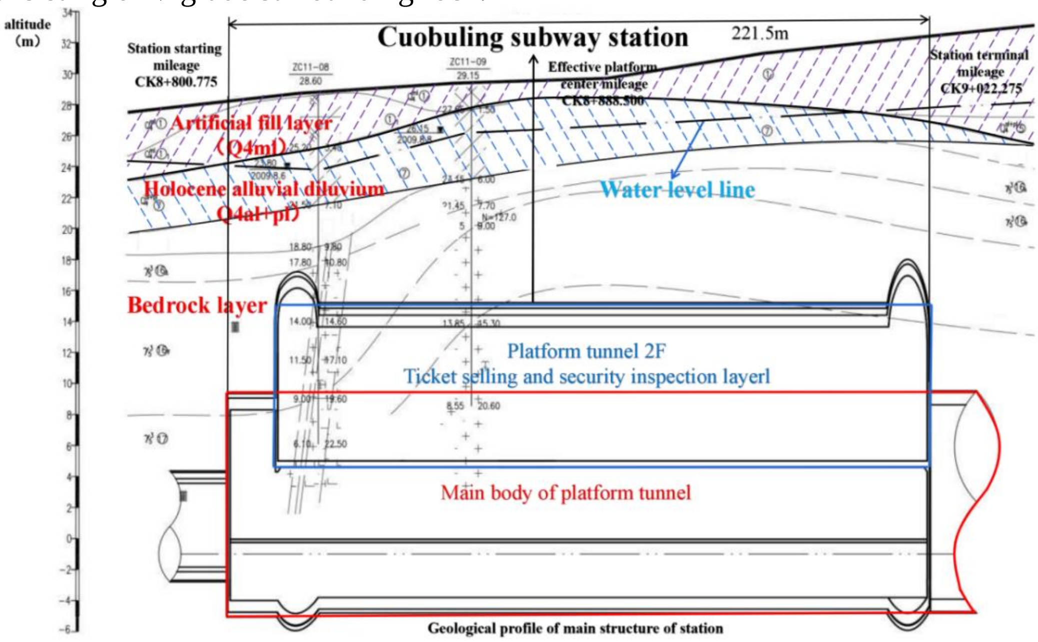

Figure 2: Geological cross-section of cuobuling subway station

3. Settlement Analysis Based on Numerical Simulation

The learning algorithm of the BP neural network has been widely used in various engineering fields in recent decades due to its complex output and input relationships, providing a new method for solving nonlinear problems and simulating control processes of unknown systems. Nevertheless, the drawbacks of the BP neural network are mainly slow convergence speed and susceptibility to local minima due to its calculation based on the gradient method. The numerical simulation process using the MIDAS software has the characteristics of high authenticity in reproducing the real construction site, and its randomness, authenticity, and global nature have become one of the important methods for researchers to study tunnel excavation. Combining numerical simulation to correct the drawbacks of the BP neural network algorithm can achieve complementary advantages.

3.1. Establishment and Simplification of the MIDAS Model

Based on the special geological conditions of the Cuobuling Station in Qingdao Subway, a MIDAS station model was established. Combining geological exploration data, parameters were established as shown in Table 1, and different rock layers were established, with initial support parameters taken from actual field data. The model terrain referenced the actual topography of the Cuobuling subway station platform, and the tunnel length was set to 60m with a step size of 0.5m, and the tunnel model was established as shown in Figure 3.

Table 1: Soil layers and parameters for shotcrete calculation

Soil Layer Type	Elastic Modulus E (GPa)	Compressive Modulus E (MPa)	Poisson's Ratio μ	Unit Weight γ (KN/m^3)	Unit Weight C (MPa)	Friction Angle Φ
(Fully weathered layer (artificial fill layer Q4ml)	—	11	0.32	17.1	1.2	8
Moderately weathered layer (Holocene alluvial layer Q4al+pl)	—	300	0.22	20.3	14	21
Hard rock layer (bedrock layer mainly composed of late granite γ53)	45000	—	0.2	26	20	42
Initial support (shotcrete)	80000	—	0.2	23	—	—

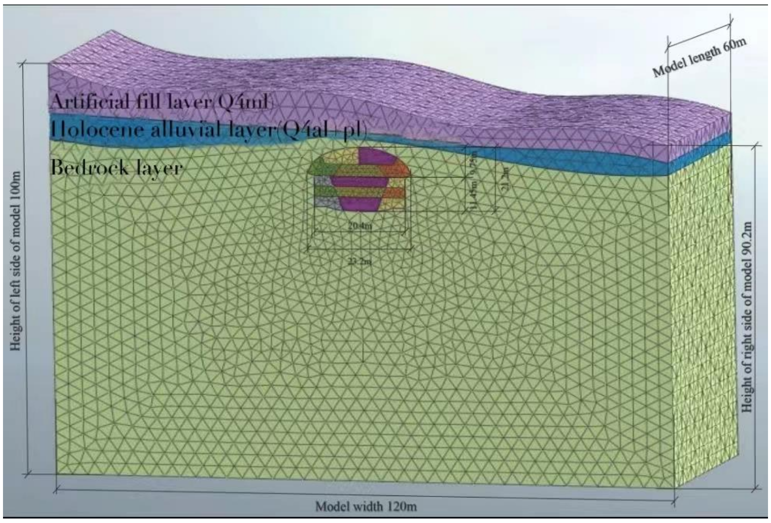

Figure 3: MIDAS model

The entire process was numerically simulated with simultaneous construction and support. The top five pilot tunnels were defined as the upper section pilot tunnels, and the bottom nine pilot tunnels were defined as the lower section pilot tunnels. The simulation was carried out according to the excavation sequence of different pilot tunnels, with a total tunnel length of 60m and a step size of 1m. After the previous layer of pilot tunnel was excavated for 10m, the next layer of pilot tunnel began excavation until all were connected from top to bottom.

3.2. Comparison and Analysis of Settlement Data and Field Measurements

The surface settlement data was analyzed at the starting point of the tunnel's centerline. As construction progressed, the surface settlement data was plotted as a curve over time. The on-site data of monitoring point DBC10-06 along the tunnel centerline was taken, which was located near the tunnel axis and the tunnel excavation had reached below this point in early November 2018. The data was also plotted as a curve, as shown in Figure 4.

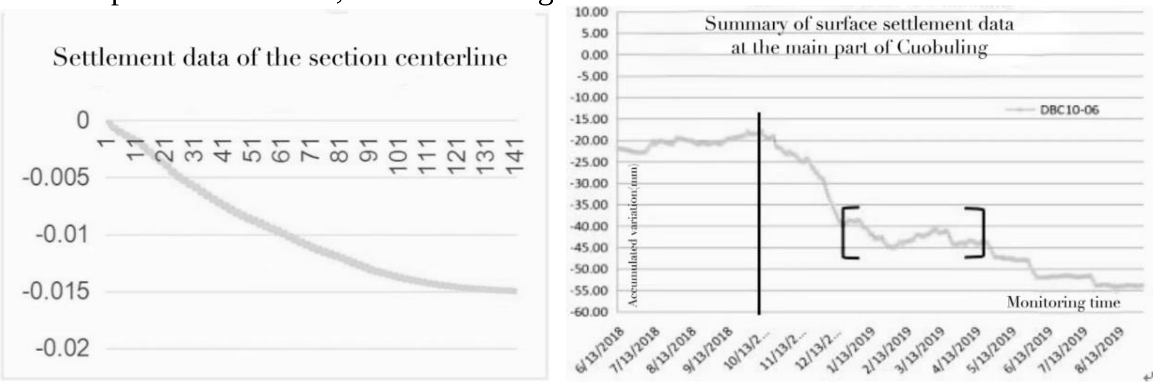

Figure 4: Settlement curves at the starting point of the tunnel centerline and monitoring point DBC10-06

As shown in the figure, MIDAS can simulate the general pattern of tunnel settlement, and its curve trend is the same as the measured data. However, the simulated settlement data is only 15mm, while the measured settlement data reaches 35mm, and the actual settlement curve trend is not reflected in the simulated curve. Since the simulation simplifies many of the problems faced in actual working conditions, it cannot reflect the stage characteristics of the actual project.

4. Modified Model Based on BP Neural Network

4.1. Improvement of BP Algorithm

The combination of MIDAS numerical simulation results and BP neural network algorithm is to optimize the initial weight of BP neural network and establish a surface settlement prediction model based on the improved BP neural network. The tunnel crown settlement data caused by the unloading of the platform construction was taken as the input variable of the BP neural network, and the surface settlement data monitored in real-time at the same period was taken as the output variable of the network. The topology of the BP neural network was selected as a double hidden layer network. After the BP neural network model was established, the post-2019 tunnel construction settlement data was taken as the model verification, and three measuring points along the tunnel axis were selected for settlement analysis, as shown in Figure 5.

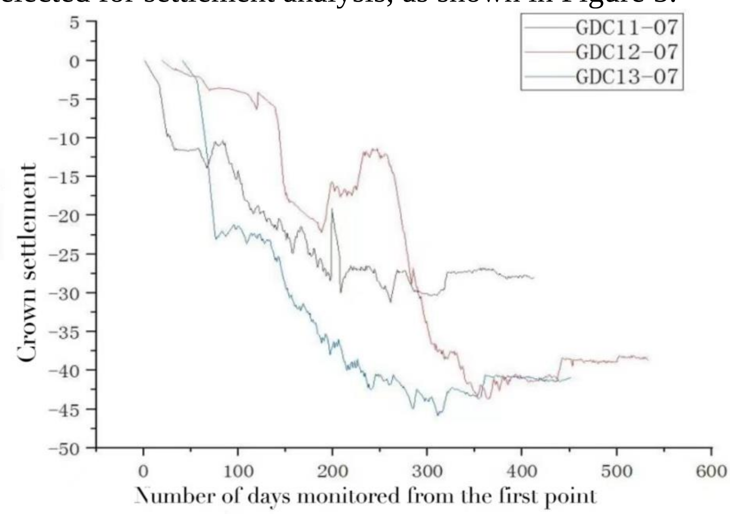

Figure 5: Crown settlement data at the three main monitoring points

In the application of neural networks, once the training samples and network structure are determined, the error is completely determined by the weights of the network (W). Therefore, in order to minimize the network error (E), new network weights (W) must be continuously sought during the training process. The definition of E (network error) is:

$$E = \frac{1}{2}\sum_{i=1}^{N}(d_i - y_i)^2 \tag{1}$$

Where:

d_i——ideal network output value; y_i——actual network output value

The minimized network error can be expressed as:

$$Emin(W) \tag{2}$$

Where:

$W = (w_1, w_2, \cdots; w_i)^T; w_i \in [a_i, b_i]; i=1,2, \cdots; l$

Where l is the number of elements in the optimized W vector, and E is the network error value corresponding to the objective function value of W.

During the optimization process of the data, the BP algorithm can be solved using MATLAB software. To improve the accuracy of settlement data prediction, a hybrid calculation method was designed by incorporating MIDAS simulation data into the calculation. This algorithm mainly uses the numerical simulation results to optimize the initial weight values of W, and then uses the BP algorithm to iteratively optimize the weights. The calculation method involves five steps, as shown in Figure 6, and the corresponding Matlab programming parameters are shown in Table 2.

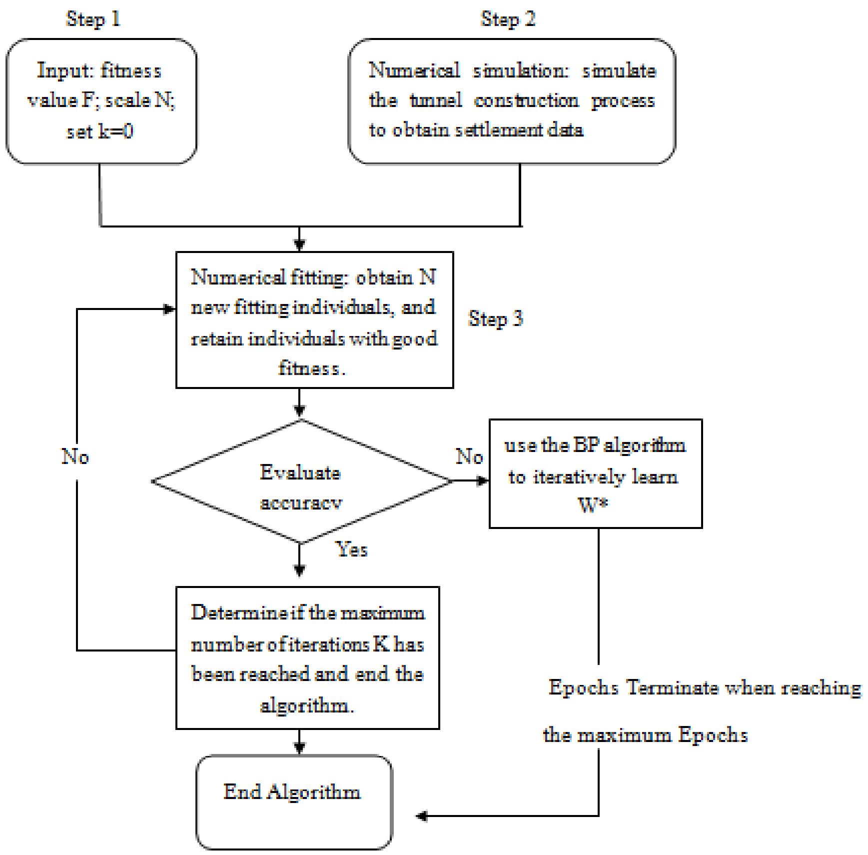

Figure 6: Iterative optimization of weights using BP algorithm

Table 2: MATLAB programming parameters

Activation function	Sigmoid function
Parameter N	30
Crossover probability P_c	0.6
Mutation probability P_m	0.1
Maximum number of iterations K	500
Accuracy ε	0.005
Maximum number of iterations Epochs	1000

The model was run five times with repeated calculations, and the optimal evolution process of the chromosome is shown in Figure 7.

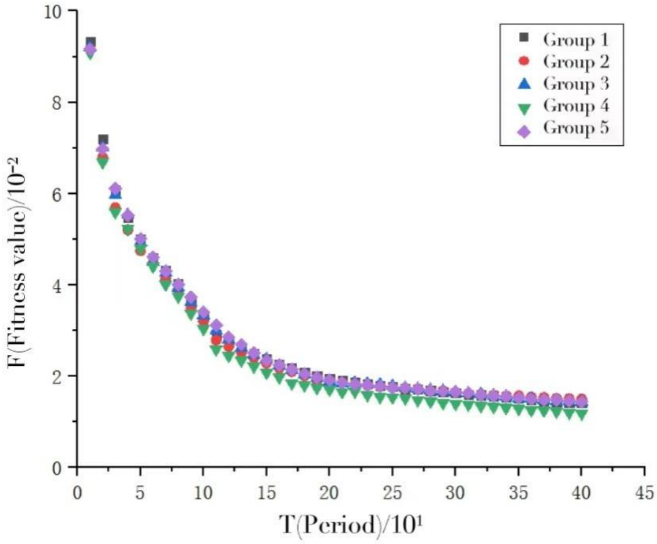

Figure 7: Optimal evolution process of chromosomes

From Figure 8, it can be seen that after five consecutive network calculations, the average fitness value of the objective decreased from 9.3×10^{-2} to 1.2×10^{-2}, and all five sets of data showed a similar decreasing trend without significant fluctuations.

Taking the third calculation as an example, the optimal network weights after fitting Midas were used in the BP neural network training. The two curves are shown in Figure 8.

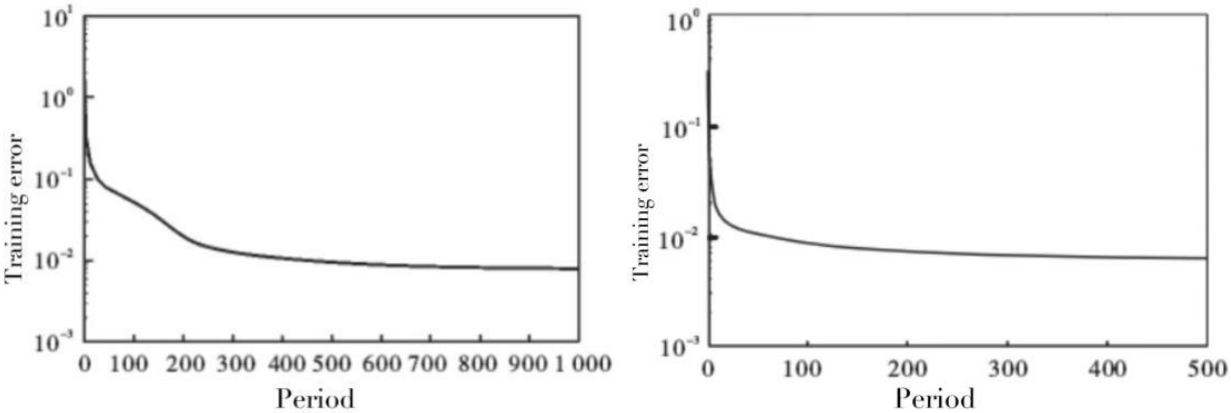

Figure 8: Curve of conventional network weight training and curve of optimal network weight training after fitting Midas

From the above figure, it can be seen that the curve of the network weights processed by the best chromosome is smoother than the original curve, and there is no oscillation phenomenon. This indicates that the combination of numerical simulation and BP neural network is more stable during the convergence process, and the error is stable within 0.1, which is much smaller than the conventional BP error.

After 100 iterations of the BP network fitted with numerical simulation, the fitting error was around 0.0085, while the original BP network error was around 0.079. This indicates that the BP neural network significantly reduces the error after fitting numerical simulation data and can be more effectively applied to the prediction process of surface settlement.

4.2. Validation of Prediction Model

The field measurement data and fitted data for the same time period were taken, as shown in Figure 1. The measured data showed severe fluctuations and large differences between monitoring points without obvious regularity. The post-fit residual test was used to verify the accuracy of the fitting result, and formula (3) was obtained.

$$
\begin{gathered}
\bar{x} = \frac{1}{n}\sum_{T=1}^{n} x^{(0)}(T) \\
e(T) = x^{(0)}(T) - \hat{x}^{(0)}(T) \\
\bar{e} = \frac{1}{n}\sum_{T=1}^{n} |e(T)|
\end{gathered}
\tag{3}
$$

Where:

$x^{(0)}(T)$——Measured surface settlement data at time T;

$\hat{x}^{(0)}(T)$——Fitted data from the neural network;

$\bar{x}$ ——Mean value of measured surface settlement data;

$e(T)$——Residual at time T;

$\bar{e}$ ——Mean value of $e(T)$.

Calculate the root mean square error (RMSE) of the measured data (S_{Actual}) and the residual (S_{residual}).

$$
S_{\text{Actual}} = \sqrt{\frac{1}{n}\sum_{T=1}^{n}\left[x^{(0)}(T) - \bar{x}\right]^2}
\tag{4}
$$

$$
S_{\text{residual}} = \sqrt{\frac{1}{n}\sum_{T=1}^{n}\left[e(T) - \bar{e}\right]^2}
\tag{5}
$$

Let A be the ratio of the posterior difference between S_{residual} and S_{Actual}, and P be the probability of a small error.

$$
\text{Then } A = S_{\text{residual}} / S_{\text{Actual}}
\tag{6}
$$

$$
P = P\left\{\left|e(T) - \bar{e}\right| < 0.6745 S_{\text{Actual}}\right\}
\tag{7}
$$

Here are two evaluation indicators for the quality of the generalization results of BP neural networks, namely A and P. If the measured mean square error S_{Actual} is small and the residual mean square error S_{residual} is large, the ratio of A will be small. In the measured data of the Cuopuling platform, S_{Actual} has a large dispersion and poor regularity. Therefore, only when S_{residual} is small can it indicate that the fitting and prediction error dispersion is small. In order to make the value of A smaller, and in the case where S_{Actual} cannot be changed significantly, S_{residual} should be made as small as possible, which means that although the original data has poor regularity, the fitting and prediction amplitude is relatively small. Another evaluation indicator for the quality of BP neural network extrapolation results is the small error probability P. The smaller the value of P, the worse the computational accuracy of BP neural network, and vice versa. According to the results of A and P, the prediction results can be classified into four categories in traditional accuracy classification, as shown in Table 3.

Table 3: Classification table of prediction results based on accuracy

Accuracy Level	Accuracy Level	Good	Fair	Poor
A	<0.35	<0.5	<0.65	≥0.65
P	>0.95	>0.8	>0.7	≤0.7

Input the actual settlement measurement data from the construction phase of Cuobuling subway station platform from October 2018 to February 2019 into the BP neural network model, and process the fitted model with the posterior difference test method. The results obtained are shown in Table 4.

Table 4: The data testing results using the posterior difference test method

Date	October 2018	November 2018	December 2018	January 2019	February 2019
S_{Actual}	0.0191	0.0302	0.0557	0.0613	0.0667
S_{residual}	0.0039	0.0054	0.0089	0.0095	0.0103
A	0.204	0.179	0.160	0.155	0.154
P	1	1	1	1	1

According to the results of testing the data using the posterior difference test method in Table 4, it can be seen that from October 2018 to February 2019, the ratio *A* of residual fitted data to the combined simulated data is all less than 0.35, and P is always 1. According to the prediction result level classification table, the BP neural network model belongs to the level 1 very good type, so the prediction model has strong generalization ability and high accuracy.

5. Application of the Prediction Model

Accurate prediction of the settlement of the ground and tunnel arch during subway tunnel construction has an important impact on the safe construction of the tunnel and the safety of surrounding buildings. Taking two sets of data on the arch settlement on the central axis of the tunnel, the data set with the largest settlement during construction (-22.5mm) and the data set with the smallest settlement (-19.7mm) are selected. Twelve sets of data are output from the BP neural network for training based on their 10% difference value, and a simulation result is obtained. The improved BP neural network curve is plotted and compared with the MIDAS simulation curve and the actual settlement curve measured by the DBC10-06 measuring point for analysis, as shown in Figure 9.

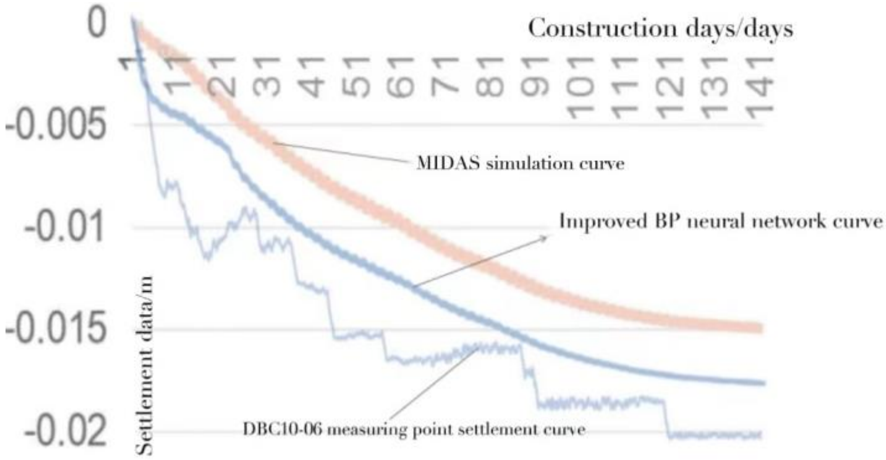

Figure 9: Simulation and simulation result curve

As shown in Figure 9 the BP neural network curve modified by numerical simulation has the same settlement law as the settlement curve obtained by MIDAS simulation. However, the improved BP neural network curve is closer to the settlement curve of the actual measured DBC10-6 monitoring point, which can reflect the characteristics of the monitoring point's rapid settlement in the initial stage of construction. Unlike the simulated value, the actual factors affecting the ground settlement data are many and have large fluctuations and poor regularity. In addition to the ground settlement caused by tunnel construction, changes in settlement values can also be caused by stratum loss and precipitation consolidation. Compared with pure numerical simulation or pure BP neural network prediction curves, the BP network fitting process is more in line with the actual measured data, which analyzes the settlement caused by various factors during construction and obtains more regular results.

6. Conclusions

Based on previous research, this paper discusses the feasibility and practicality of using numerical simulation and BP neural network for surface settlement analysis and prediction in the geological environment of Cuobuling station on Qingdao metro line 4. The application results show that the improved BP neural network has not only prediction ability and anti-interference ability but also good nonlinear expression ability. It has high accuracy in predicting the settlement during the subway tunnel construction phase and the following conclusions are obtained. (1)Through fitting the numerical simulation data of Midas with the measured data, the initial weight of the BP neural network for network calculation can be optimized, which not only solves the problem of poor regularity of measured data, inaccurate numerical simulation accuracy and slow convergence and easy to fall into local minima of traditional BP neural network, but also establishes a more accurate surface settlement model. (2)After testing the fitted BP neural network model using the posterior difference method, the test results show that the model has high accuracy and precision, can effectively simulate and predict the surface settlement data during the tunnel construction phase, and obtain quantitative data. The application of this model to simulate and predict the unconstructed section can obtain results similar to the measured regularity.

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