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The Application of Wavelet Neural Network in the Settlement Monitoring of Subway

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Abstract:
The settlement monitoring of subway runs through the entire construction stage of subway. It is very important to predict the accurate settlement value for construction safety of subway. In this paper, the wavelet transform is used to denoise the settlement data. The auxiliary wavelet neural network, embedded wavelet neural network and single BP neural network are applied to predict the settlement of Tianjin subway. Compared with single BP neural network and auxiliary wavelet neural network, the embedded wavelet neural network model has a higher accuracy and better prediction effect. The embedded wavelet neural network is more valuable than the BP neural network model so it can be used in the prediction of subway settlement.

Keywords: *settlement monitoring, settlement value, embedded wavelet neural network*

1. Introduction

Construction safety of subway is one of the most important aspects in the subway construction. In order to reduce the occurrence of subway construction accidents, the settlement prediction are carried out in the construction process. In recent years, many scholars have proposed various ways of the prediction of the subway settlement, for example, time series analysis method [1-4], time series based on wavelet [5], BP neural network [6] and finite element method [7]. Time series analysis method has been widely applied to the settlement prediction of subway. The accuracy, feasibility and trend of the prediction are evaluated after the prediction settlement value and the measured value compared and analyzed.Wavelet neural network is a common prediction method, which has been widely used in the prediction of building settlement [8, 9], debris retaining dam settlement [10], large section settlement of tunnel [11] and surface settlement after coal mining [12].

The prediction process of time series analysis method is more complex. The settlement observation points would have good predictions only if they have large number of observations, large deformation amount, or great subsiding speed [4]. Wavelet neural network method, with a simple structure, has a strong learning ability and fast convergence speed, as well as more accurate result of the same task [13]. In consequence, wavelet neural network is attempted to be applied to the prediction of the settlement of Tianjin Subway in this paper. The wavelet neural network method is expected to expand subway settlement prediction. As a continuation, the accuracies and the prediction results of single BP neural network, auxiliary wavelet neural network and embedded wavelet neural network are evaluated by comparing the predictive value with the measured value.

1.1. Instruction of Wavelet Neural Network Model

This section first introduces the basic theory of neural network, wavelet analysis and wavelet denoising, On the basis of these theories, the theory of the combination of wavelet transform and neural network is introduced.

1.1.1. Instruction of BP Neural Network

BP neural network is one of the most widely used neural networks. It is a kind of multilayer feed forward network which is trained by the error back propagation algorithm.

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Momentum BP algorithm is introduced in the gradient descent algorithm based on momentum factor:$\eta(0 < \eta < 1)$.

$$\Delta x(k+1) = \eta \Delta x(k) + \alpha(1-\eta)\frac{\partial E(k)}{\partial x(k)} \tag{1}$$

$$x(k+1) = x(k) + \Delta x(k+1) \tag{2}$$

The correction value of the momentum BP algorithm is affected by the previous corrected results. $\Delta x(k+1)$ is opposite to the sign of $x(k)$ in the formula (2) when the current correction value is too large. $\Delta x(k+1)$ is the same as the symbol of $x(k)$ in the formula (2) when the current correction value is too small. The aim of the momentum BP algorithm is to increase the correction in the same gradient direction. The momentum of the same gradient direction becomes larger when the momentum factor $\eta(0 < \eta < 1)$becomes larger [14].

1.1.2. Instruction of Wavelet Analysis and Wavelet Denoising

The main objective of wavelet analysis is the study of the representation of the function: Decomposition and reconstruction. The function which is decomposed into "basic functions" can be obtained by the translation and extension of the wavelet function. The wavelet function itself has a very good smoothness and locality. When we describe the function by the decomposition coefficient, we can analyze the local properties and the global properties of the function [15]. Wavelet denoising has been widely used in many fields. Since threshold denoising has good denoising effect and easy operation condition, it becomes one of the most important methods of wavelet denoising. The denoised signal is obtained by wavelet reconstruction. A one-dimensional signal model with noise can be expressed as follow [16]:

$$f(t) = s(t) + \sigma e(t) \tag{3}$$

Among them, $\mathrm{f(t)}$ for the noisy signal, $\mathrm{e(t)}$ for the noise, $s(\mathrm{t})$ for the original signal.

1.1.3. Instruction of Wavelet Neural Network

Wavelet transform has local time-frequency characteristics and focusing characteristics. Artificial neural network which has great adaptability, learning, robustness, and fault tolerance is a powerful tool to deal large scale problems. The combination of the advantages of both method is worth of our attention.

Zhang Qinghua, et al., (1992) put forward the concept and algorithm of wavelet neural network [15]. At present, the combination of neural network and wavelet transform mainly has two kinds: Loose combination (auxiliary wavelet neural network), the data which are denoised by wavelet transform are used as the input vector of the neural network. Tight binding (embedded wavelet neural network), the wavelet transform is embedded into the neural network. The wavelet function is taken as the activation function of the hidden layer neurons of neural network [15, 17]. When the input signal sequence is $\mathrm{x_i}(\mathrm{i} = 1,2,\cdots,\mathrm{k})$, the formula for the hidden layer is as follow [18]:

$$\mathrm{h(j)} = \mathrm{h_j}\left[\frac{\sum_{\mathrm{i=1}}^{\mathrm{k}} \omega_{\mathrm{ij}}\mathrm{x_i} - \mathrm{b_j}}{\mathrm{a_j}}\right] \quad \mathrm{j} = 1,2,\cdots,\mathrm{l} \tag{4}$$

Notes:
$\mathrm{h(j)}$ is the output value of the first j node of the hidden layer.
ω_{ij} is the connection weights between the input layer and the hidden layer.
$\mathrm{b_j}$ is the translation factor for wavelet basis function $\mathrm{h_j}$.
$\mathrm{a_j}$ is expansion factor for wavelet basis function $\mathrm{h_j}$.
$\mathrm{h_j}$ is the wavelet basis function.

In this paper, the morlet function is used as the wavelet basis function [18].

$$\mathrm{y} = \cos(1.75\mathrm{x})\mathrm{e}^{-\mathrm{x}^2/2} \tag{5}$$

2. Results and Discussion

Taking the North Park Station of Tianjin Subway Line 6 as an example, we use wavelet neural network model to predict the settlement based on the surface subsidence monitoring data. In order to show the good prediction effect of wavelet neural network on the settlement data in different periods, the short-term, medium-term and long-term settlement data are selected, which has 28, 55, 115 periods, respectively. For the 28 periods, the settlement data of the first 25 periods are used to establish the model. and the other 3 periods are used for verification. For the 55 periods, the first 52 periods are used to establish the model, and the other 3 periods are used for validation. For the 115 periods, which has larger amount of data, the first 110 periods are used to establish the model and the other 5 periods are used for validation.

2.1. Results of Wavelet Denoising

The effect of wavelet denoising on subway subsidence data is determined by the mean square error (MSE). In order to obtain the best denoising effect, different wavelet functions, decomposition levels and threshold methods are used in the paper. We find the best way to denoise by a large number of comparative simulation experiments. MSE is the minimum and the denoising effect of subway settlement data is the best when the wavelet function is db5, the number of decomposition layer is 3-layer and the threshold selection method is minimaxi. The effect of three different settlement points' data before and after denoising is shown in Figure 1, Figure 2, and Figure 3.

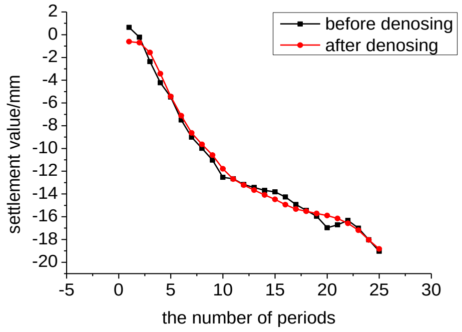

Figure 1. The Contrast Diagram of a Point to Denoise before and after

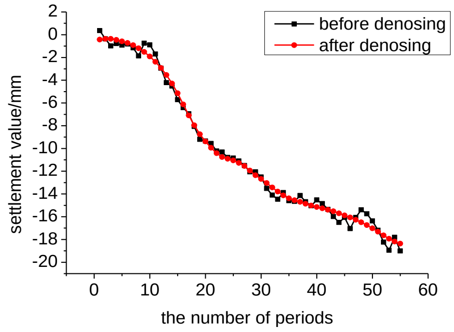

Figure 2. The Contrast Diagram of b Point to Denoise before and after

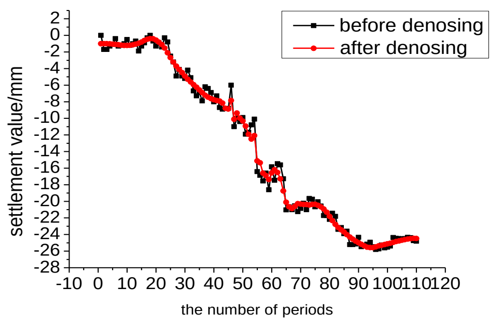

Figure 3. The Contrast Diagram of c Point to Denoise before and after

2.2. Results of Settlement Prediction

With the comparison and analysis of experimental data, we determine to use the 3-layer neural network (input layer, hidden layer, output layer). The number of neurons of the input layer and the output layer is determined according to the number of samples. The number of hidden layer nodes corresponding to three different points (a, b, c) are 6, 9 and 11, respectively. The training function is set as traindm, the learning function is learngdm, the learning rate is 0.01, the number of training times is 10000, the training accuracy is 10-5, and the momentum factor is 0.75. Initial weights and thresholds are generated randomly. The activation function of hidden layer of BP neural network and auxiliary neural network is set as sigmoid function. The activation function of hidden layer of embedded neural network selects the morlet function. The predictive value of three different points (a, b, c) by using single BP neural network, auxiliary neural network and embedded wavelet neural network are shown in Figure 4, Figure 5, Figure 6.

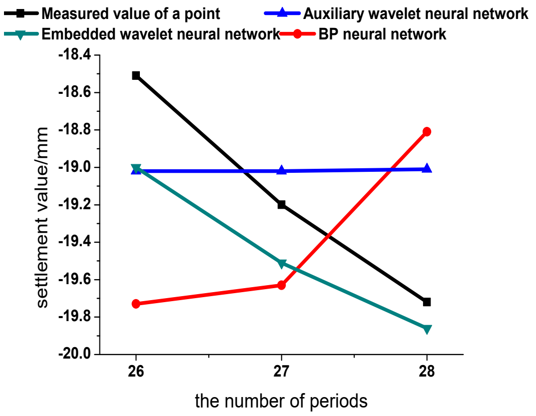

Figure 4. Measured Value and Predictive Value of a Point (Unit /mm)

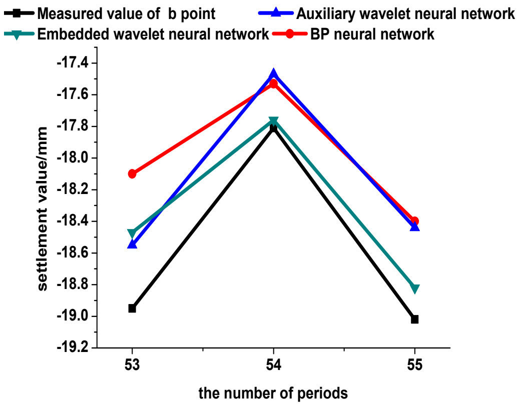

Figure 5. Measured Value and Predictive Value of b Point (Unit /mm)

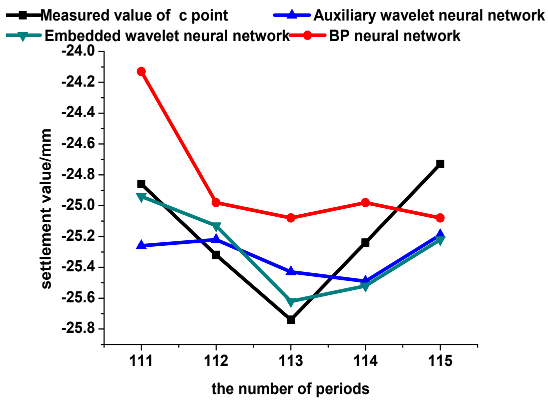

Figure 6. Measured Value and Predictive Value of c Point (Unit /mm)

2.3. Evaluation of Prediction Accuracy

The evaluation of the prediction accuracy of subway settlement includes four aspects: evaluation of model accuracy, absolute error, mean error and mean absolute error. They are shown in Table 1, Table 2, Table 3, Table 4, respectively.

$$\text{Accuracy of the model} = \sqrt{\frac{\sum(\text{predictive value}-\text{measured value})^2}{\text{n}-1}} \tag{6}$$

Table 1. The Accuracy of the Three Prediction Models (Unit /mm)

Point	Accuracy of single BP neural network model	Accuracy of auxiliary wavelet neural network model	Accuracy of embedded wavelet neural network model
A	1.12	0.63	0.42
B	0.77	0.55	0.37
C	0.56	0.37	0.31

Table 2. The Maximum Absolute Error and the Minimum Absolute Error of the Three Prediction Models (Unit /mm)

Point	Single BP neural network		Auxiliary wavelet neural network		Embedded wavelet neural network	
	Maximum absolute error	Minimum absolute error	Maximum absolute error	Minimum absolute error	Maximum absolute error	Minimum absolute error
A	1.22	0.43	0.71	0.18	0.49	0.14
B	0.85	0.28	0.58	0.34	0.48	0.05
C	0.73	0.26	0.46	0.10	0.49	0.08

Table 3. The Mean Error and the Mean Absolute Error of the Three Prediction Models (Unit /mm)

Point	Single BP neural network		Auxiliary wavelet neural network		Embedded wavelet neural network	
	Mean error	Mean absolute error	Mean error	Mean absolute error	Mean error	Mean absolute error
a	0.25	0.85	-0.13	0.47	0.31	0.31
b	-0.58	0.58	-0.44	0.44	-0.24	0.24
c	-0.33	0.47	0.14	0.30	0.11	0.23

Table 1 shows that the model accuracies of the two wavelet neural network methods are higher than the single BP neural network model. The model accuracy of the embedded wavelet neural network is higher than the auxiliary wavelet neural network model. The highest and lowest model accuracies of single BP neural network are 0.56 mm and 1.12 mm, respectively. The highest and lowest model accuracies of embedded wavelet neural network are 0.31 mm and 0.42 mm, respectively. In addition, with the increase of training samples, the accuracy of the three models will be improved, and the effect will be better.

As we can see in the Table 2, the maximum absolute error of the two wavelet neural network prediction models is less than 1 mm. The maximum and minimum absolute errors of the two wavelet neural networks are smaller than those of single BP neural network. The maximum and minimum absolute errors of the embedded wavelet neural network are 0.49mm and 0.05mm, respectively. The maximum and minimum absolute errors of a single BP neural network are 1.22 mm and 0.26mm, respectively.

As can be seen from the Table 3, the mean error and the mean absolute error of the three prediction models are less than 1 mm. For b, c points, the mean errors of the embedded wavelet neural network are -0.24 mm, 0.11 mm, respectively. For a, b, c points, the mean absolute error of the two wavelet neural network is less than that of the single BP neural network. The embedded wavelet neural network in the three prediction models has the smallest mean absolute errors of 0.31 mm, 0.24 mm, 0.23 mm, respectively.

3. Conclusion

In this paper, a single BP neural network and two kinds of wavelet neural network are applied to Tianjin Subway settlement prediction, and the following conclusions are drawn:

1) With the increase of the number of training samples, the accuracy of the three models will be improved.

2) Embedded wavelet neural network in three kinds of prediction models has the best model accuracy, absolute error, mean error and mean absolute error. The model accuracy of embedded neural network is less than 0.5mm. The maximum absolute error is less than 0.5mm.

In general, the embedded wavelet neural network has a good prediction effect in the settlement prediction of subway which will expand the methods for subway settlement prediction.

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