Prediction of Horizontal Displacement of Foundation Pit Based on NAR Dynamic Neural Network

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Abstract. NAR dynamic neural network has the function of feedback and memory, which can be effectively used in time series data modeling. Taking the actual horizontal displacement of a foundation pit in Qingdao as the experimental data, the time series prediction model of the horizontal displacement of the foundation pit is established by NAR dynamic neural network. The model is applied to predict the horizontal displacement of foundation pit, and compared with grey prediction, support vector machine and BP neural network. The results show that the prediction accuracy of NAR dynamic neural network model is high. It has strong stability and can be effectively applied to the prediction of foundation pit displacement.

1. Introduction

With the continuous improvement of the level of urbanization in China, urban construction has entered a period of rapid development. A variety of ultra-high buildings have sprung up rapidly, and more and more deep foundation pit projects have been built [1]. With the increasing depth and area of excavation, the stability and safety of the foundation pit are increasingly concerned by the society. Accurate prediction of the deformation of the foundation pit has become a very important work. In recent years, BP neural network, support vector machine and grey prediction are widely used in the prediction of foundation pit displacement, which have achieved good prediction results [2-3]. However, the deformation of foundation pit has great randomness, uncertainty and complexity. In some cases, the grey prediction model can not meet the accuracy requirements [3-4]. BP neural network and support vector machine model need to adjust more parameters, and their accuracy is also greatly affected by the parameters. In view of this, this paper proposes to predict the horizontal displacement of foundation pit based on the NAR dynamic neural network model, and at the same time compares the accuracy with the prediction values of BP neural network, grey prediction and support vector machine, so as to verify the effectiveness and superiority of the proposed NAR model, and provide a certain reference for the prediction of the horizontal displacement of foundation pit.
2. NAR neural network model

2.1. Structure of NAR model
NAR neural network is composed of input layer, hidden layer, lag layer and output layer. Its basic structure is shown in Figure 1.

![Figure 1. NAR neural network structure](image)

NAR neural network model can be described as follows:

\[ y(t) = f(y(t-1), y(t-2), y(t-3), \ldots, y(t-d)) \]  

(1)

In this formula: \( d \) is the delay order, \( t \) is the discrete time, \( y(t-n)(n=1,2,\ldots,n) \) is the model input, \( y(t) \) is the model output, and \( f(\cdot) \) is the neural network model structure.

Using the NAR neural network model, the NAR neural network is first transformed into a feedforward neural network, with which static neural network functions are directly used. Then, this model is transformed into a parallel model, through which the expected output is fed back to the input, so that the prediction results are more accurate.

2.2. Prediction method of NAR neural network model
The recursive prediction method is used in NAR model prediction. The core of this prediction method is to use the prediction value in the first step in a cycle. Compared with the direct prediction method, the recursive prediction error is relatively small [6-7].

For NAR model: \( y(t) = f(y(t-1), y(t-2), y(t-3), \ldots, y(t-d)) \)

(1) When \( k = 1 \), predict \( y(t_n) \) and get the first prediction value;

(2) Predict \( y(t_{n+1}) \), add the prediction value in step (1) to the original sample to form a new sample:

\[ y(t_n-d), \ldots, y(t_n-2), y(t_n-1), y(t_n) \]  

(2)

Then we can get the second prediction value \( y(t_n+1) \);

(3) Using nonparametric model to get the third step prediction value for the new samples, and then go back and forth until the required step prediction value is obtained.

2.3. A method to determine the order of NAR model
For the future time series, NAR model needs to determine the number of delay variables in the delay function, that is, to determine the order of NAR model. Adopt leave one out cross validation method to determine model order [8].

Define the performance of cv measurement model:

\[ CV = \frac{1}{m} \sum_{i=1}^{m} L(y_i, \hat{f}^{-1}(x_i)) \]  

(3)
In this formula: $m$ is the number of samples; $y_i$ is the observation value of the $i$ sample; $\hat{f}^{i-1}$ is the predicted value of the model established by removing the sample $i$ and the rest $m-1$ samples.

2.4. Construction and test of prediction model based on NAR neural network

Step 1: According to the cross validation method, the order of the model is determined for the measured displacement data. CV = 2 is obtained by calculation, and the first two values are used to predict the third value;

Step 2: Configure data, set training data and verification data respectively, take 80% and 20% of all data respectively, and convert the data into network applicable data type according to preparets function of MATLAB platform after data distribution;

Step 3: Configure the learning network. The size of the hidden layer is 1 and the number of neurons is 5. Train the network with the train() function. The learning method is trainbr function;

Step 4: Verify whether the network model meets the performance accuracy requirements, if not, continue to carry out step 3 network training;

Step 5: Use the network that has been trained and meets the accuracy requirements to predict, output the predicted value and check the prediction error.

3. Project example and result analysis

The original data sequence is shown in Figure 2.

![Figure 2. Change curve of foundation pit displacement observation value](image1)

![Figure 3. Fitting and fitting error of NAR network training samples](image2)
The data of measured horizontal displacement of foundation pit is processed, imported into Matlab, and the training feedback time series is created. All training data are processed by Bayesian regularization to meet the data format requirements of NAR network. Select the first 40 periods of measured data as training samples, and create NAR nonlinear autoregressive network. Test the training samples with the network completed by the training data, obtain the predicted value of the training data, and get the error of the measured value and predicted value of the training data, as shown in Figure 3. Select the measured values of the last 7 periods as the test data, test the selected test samples with the trained NAR network, and obtain the predicted values and errors of the test samples, as shown in Figure 4.

\[ \text{Figure 4. NAR network test sample prediction and prediction error} \]

From Figure 3, it can be seen that the fitting error of the curve is between 0.2-0.4, and the error is relatively small, so it can be seen that the NAR model has a good fitting effect on the nonlinear curve. From the prediction curve in Figure 4, it can be seen that the NAR model can well predict the value of test samples, and the prediction error is in the range of 0-0.15, which can meet the actual engineering requirements.

\[ \text{Figure 5. Correlation coefficients of training samples, test samples and data sets} \]
Figure 6. Error autocorrelation

In order to verify the feasibility and accuracy of NAR prediction model, the correlation coefficients of training samples, test samples and data sets and the error autocorrelation of NAR network are obtained. As shown in Figure 5 and Figure 6. The correlation coefficient $R = 0.99886, 0.9993, 0.9997$ of training samples, test samples and data sets, and the closer the correlation coefficient is to 1, the better the fitting effect is. Figure 6 is the autocorrelation analysis of the NAR model. It can be seen that although the autocorrelation of the NAR model fluctuates up and down, it is generally within the confidence interval, which also shows that the NAR model is reasonable to predict the time series of data.

In order to further verify the accuracy of NAR prediction model, it is compared and analyzed with the other three prediction models, which are grey prediction, BP neural network and support vector machine. The calculation results of these three models are shown in Figure 7, and the predicted value and relative error are shown in Table 1.

Table 1. Comparison of predicted values of the model (Unit length: mm)

| sequential | Measured value | gray prediction value | Support vector machine predicted value | BP neural network predicted value | NAR Network predicted value |
|------------|----------------|-----------------------|---------------------------------------|----------------------------------|-----------------------------|
| 1          | 11.31          | 11.4076               | -0.0976                               | 11.3800                          | -0.0700                     |
| 2          | 11.39          | 11.5225               | -0.1325                               | 11.4546                          | -0.0646                     |
| 3          | 11.39          | 11.5486               | -0.1586                               | 11.5336                          | -0.1436                     |
| 4          | 11.50          | 11.6747               | -0.1747                               | 11.6542                          | -0.0642                     |
| 5          | 11.58          | 11.7254               | -0.1454                               | 11.7326                          | -0.1526                     |
| 6          | 11.63          | 11.7424               | -0.1124                               | 11.7356                          | -0.1056                     |
| 7          | 11.74          | 11.7688               | -0.0280                               | 11.7479                          | -0.0079                     |
It can be seen from figure 8 and table 1 that the change trend of predicted value of NAR model is basically consistent with the measured value, and the minimum relative error is 0.0020, the maximum is 0.1332, the average relative error is 0.048, the average error of grey model is 0.121, and the relative error of support vector machine and BP neural network is 0.087, which shows that NAR model can be effectively used for prediction of horizontal displacement of foundation pit.

4. Conclusion

(1) The time series prediction model of the horizontal displacement of the foundation pit is established by using the NAR dynamic neural network. Through the change curve of the observed value of the displacement of the foundation pit, it can be seen that the change of the horizontal displacement of the foundation pit has an obvious nonlinear upward trend. The prediction results show that the NAR dynamic neural network has a good nonlinear mapping ability and self adaptability.

(2) When building the model, the number of hidden layer neurons and lag order should not be too much, otherwise it will lead to over fitting, otherwise, it will lead to incomplete fitting. For the established model, the correlation coefficient R and the error autocorrelation coefficient are used to detect the network performance, further reducing the prediction error influence caused by the uncertainty of the model itself.

(3) In terms of prediction accuracy, NAR dynamic neural network prediction model is obviously better than grey prediction, support vector machine and BP neural network, which has strong prediction ability and accuracy and can be better applied to foundation pit displacement prediction.

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