The Application of Adaptive BP Neural Network on Numerical Prediction on Tunnel Vault Subsidence Based on the Moving Average

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ABSTRACT: Tunnel vault subsidence is a very complex nonlinear dynamic system whose feature is difficult to describe accurately by traditional methods. In this paper, the moving average model of time series and the adaptive BP neural network are adopted to build the model, which use smoothing method of time series to curb and weaken the error in field surveying data, in an effort to reduce the numerical fluctuations of time series and use the adaptive learning rate and the momentum method to improve weaknesses of easily trapped into local minima, slow convergence and other shortcomings in the BP neural network. The prediction examples show that the model based on the moving average and the adaptive BP neural network can effectively restrain and weaken the measurement error and the method has features of simple, fast convergence and high accuracy prediction. Therefore, this method can be widely used.

KEYWORDS: Time series, Moving average model, Neural network, Tunnel, Vault subsidence

1 INTRODUCTION

The tendency of variation of the vault subsidence is one of the key factors determining the secondary lining time of the tunnel. It is very important for determining appropriate secondary lining time and ensuring the safety of tunnel construction, and so forth, to accurately predict the timing tunnel crown settlement. After the tunnel excavated, rock stress will re-distributed and the tunnel crown will keep deforming, which is a complex nonlinear dynamic system difficult to reveal its inherent rules by traditional methods and techniques. Nevertheless, the new neural network theory developed over the last decade possesses many good features such as self-organization, adaptivity, fault tolerance etc., which is suitable to deal with problems with complicated information, unclear background and uncertain inference rules. Therefore, it is of high objectivity and adaptability for modeling the time series of tunnel crown settlement to use the powerful nonlinear mapping ability of the neural network [1].

However, accidental errors and systemic errors may occur during field surveying data gathering because of field conditions, measuring instruments, observers’ abilities and so forth which can cause deviations in predicted results. Therefore, the original measurement data must be smoothed which can inhibit or weaken the fluctuations of time series and lead to trend time series. At present, all the right values have the same learning rate among BP neural network models which are widely used basing on error back propagation. Therefore, all the right values vary at the same learning rate. However, in practice, some weight may be closer to the optimal value or its impact on errors is stronger than other weights. If each weight can be adjusted in an adaptive way, we would achieve higher flexibility and faster convergence [2]. In this paper, the moving average model of time series is combined with the adaptive BP neural network, in order to obtain faster convergence and higher forecast accuracy.

2 PROCESS OF SMOOTHING TIME SERIES

Smoothing is a basic method of time series. There are a variety of commonly used time series smoothing models. In this paper, the moving average model is used. Supposing \( x = \{x_1, x_2, \ldots, x_n\} \) as field surveying data, and \( M_t \) is smoothed data. Then the moving average value of point \( n \) can be calculated by:

\[
M_t = \frac{1}{n} \{x_t, x_{t-1}, \ldots, x_{t-n+1}\} \tag{1}
\]

This model has fully considered the possible impact of data before time \( t \) on data in time \( t \), and that of data in time \( t \) on data after time \( t \). There are two problems in choosing the value of \( n \) in this model: 1) if the \( n \) value is too large, after smoothing process, the variation of the value will be small when the time series varied, though the random error has been removed effectively. This means that this treatment is difficult to reflect the variation of data of time series; 2) if the \( n \) value is chosen too small, conversely, the noise in time series can not be completely eliminated, though the value varies according to smoothing process with the time series data. Therefore, in practice, the \( n \)-value should be carefully selected for data smoothing [3].

In this paper, five-point moving average model is adopted. The time series data of the beginning two points and the last two points can be obtained by the following formula:
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\[ M_1 = x_i \]  \hspace{1cm} (2)

\[ M_2 = \frac{1}{3}(x_i + x_2 + x_3) \]  \hspace{1cm} (3)

\[ M_2 = \frac{1}{3}(x_{n-2} + x_{n-1} + x_n) \]  \hspace{1cm} (4)

\[ M_n = x_n \]  \hspace{1cm} (5)

3 THEORY OF ADAPTIVE NEURAL NETWORK

3.1 BP neural network algorithm
BP network is typically consisted of an input layer, one or more hidden layers and an output layer, the structure of which is shown in Figure 1. When a group of training samples are provided to the network, activating values of neuron will be transmitted from the input layer to the output layer, passing through the middle layers, by which the input response can be obtained from each neuron of the output layer. Then, along with the direction of reducing the errors between target output and actual output, activation value spread from the output layer back to the input layer through middle layers so that connection weights can be amended layer by layer. Hence, the correcting rate of network’s response to input pattern increases constantly[3].

3.2 Shortages of BP Neural Network
BP neural network can approximate any continuous function, but there are also some flaws and shortcomings in itself: 1) all learning rate weights are the same and all weights vary with a same learning rate. Thus, convergence speed of network is slow and more training time is acquired; 2) convergence value of BP neural network is not always the global minimum value of the error plane, since a variety of local minimum points can be produced because BP neural network can, mathematically, boil down to nonlinear gradient optimization.

3.2 Improvement on BP Neural Network by Adaptive Method
Improvements made by adaptive method are as follows: on the one hand, every weight is adjusted independently in its own learning rate by adaptive method. Therefore, this method is more flexible and has a faster convergence rate. On the other hand, the momentum factor which is introduced to make learning process steady makes net learning weights more smooth by adding the average of the past weights’ variations to every new weight increment.

4 EXAMPLE ANALYZE
Now, cumulative vault subsidence observed values of point YK111+115 in a tunnel are taken as an example to explain the application of the model based on the moving average and the adaptive neural network in deformation prediction. 20 continuous cumulative vault subsidence observed values (as is shown in table 1) of this point from equal intervals are taken to compose a time series \( X = \{ x_1, x_2, \ldots, x_{20} \} \)

<table>
<thead>
<tr>
<th>Date</th>
<th>cumulative vault subsidence values (cm)</th>
<th>Date</th>
<th>cumulative vault subsidence values (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 4</td>
<td>0.322</td>
<td>April 24</td>
<td>1.198</td>
</tr>
<tr>
<td>April 6</td>
<td>0.448</td>
<td>April 26</td>
<td>1.205</td>
</tr>
<tr>
<td>April 8</td>
<td>0.502</td>
<td>April 28</td>
<td>1.33</td>
</tr>
<tr>
<td>April 10</td>
<td>0.647</td>
<td>April 30</td>
<td>1.41</td>
</tr>
<tr>
<td>April 12</td>
<td>0.671</td>
<td>May 2</td>
<td>1.52</td>
</tr>
<tr>
<td>April 14</td>
<td>0.722</td>
<td>May 4</td>
<td>1.56</td>
</tr>
<tr>
<td>April 16</td>
<td>0.916</td>
<td>May 6</td>
<td>1.59</td>
</tr>
</tbody>
</table>

Fig. 1 Neural Network Architecture
4.1 Data Smooth Processing

Cumulative vault subsidence values are smoothed by applying 5-point sliding average formula to remove measurement error. The smoothed cumulative vault subsidence values are:

\[ M = \{0.322, 0.424, 0.518, 0.598, 0.692, 0.801, 0.906, 1.009, 1.047, 1.162, 1.218, 1.265, 1.333, 1.405, 1.482, 1.546, 1.591, 1.636, 1.651, 1.71\}. \]

Comparison of pre and past smooth processing data is shown in Fig. 2.

![Cumulative vault subsidence values are smoothed by applying 5-point sliding average formula to remove measurement error. The smoothed cumulative vault subsidence values are: M={0.322, 0.424, 0.518, 0.598, 0.692, 0.801, 0.906, 1.009, 1.047, 1.162, 1.218, 1.265, 1.333, 1.405, 1.482, 1.546, 1.591, 1.636, 1.651, 1.71}. Comparison of pre and past smooth processing data is shown in Fig. 2.](image)

Fig. 2 Comparison of Pre and Past Smooth Processing Data

4.2 The Conversion of Forecast Goal and Time Sequence

In practical forecasting, the greatest impact on forecasting results comes from the former measurement data. In this paper, 20 past smooth processing cumulative vault subsidence values were used as training samples and the number of time series windows was set as 4, which meant that the fifth of measurement data would be predicted from the past four of measurement data. The segmenting method is shown in Table 2.

<table>
<thead>
<tr>
<th>4 input</th>
<th>1 output</th>
</tr>
</thead>
<tbody>
<tr>
<td>X(1),X(2),X(3),X(4)</td>
<td>X(5)</td>
</tr>
<tr>
<td>X(2),X(3),X(4),X(5)</td>
<td>X(6)</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>X(16),X(17),X(18),X(19)</td>
<td>X(20)</td>
</tr>
</tbody>
</table>

Table 2 Segmentation Method of Sample Data
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4.3 Adaptive BP Neural Network Training

A new three-layer neural network model based on BP feed-forward was adopted, in which the number of input layer neurons is four and output layer neurons is one. According to Kolmogorov criterion, hidden layer neurons are nine. We took tansig, S-type tangent function as the transfer function of network interlayer neurons and logsig, S-type logarithm function, as the transfer function of network output layer. The momentum value, m, was set as 0.8 and initial learning rate, \( \eta \), as 0.02 and average error as 0.001. After 10,000 times training, the average error of standard BP network was 0.0020905, which was still fail to reach the goal of supposed controlling error. This process is shown in Figure 3. Training of the adaptive BP neural network is fluent and convergence rate is fast and can pass through the local minimum point satisfactorily. After 176 times training, the average error of standard BP network turned out to be 0.00093024. This process is shown in Figure 4.

4.4 Prediction by Adaptive BP Neural Network

Four cumulative vault subsidence values, from May 6 to May 12, were predicted by trained neural network. The results are shown in Table 3. From the table we can draw the conclusion that: using standard BP neural network, the absolute error is less than 0.8mm and the relative error is less than 5%. Using adaptive BP neural network, however, the absolute error is less than 0.2mm and the relative error is less than 2%. Therefore, prediction by using adaptive BP neural network is more precise and more suitable for numerical prediction of tunnel vault subsidence values.

Figure 3 Training Process of Standard BP Neural Network

Figure 4 Training Process of Adaptive BP Neural Network
### Table 3 Results of Prediction

<table>
<thead>
<tr>
<th>Date</th>
<th>actual observed value (smoothed) (cm)</th>
<th>standard BP neural network predictions</th>
<th>adaptive BP neural network predictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>predictive values (cm)</td>
<td>absolute errors (cm)</td>
</tr>
<tr>
<td>May 6</td>
<td>1.598</td>
<td>1.6599</td>
<td>0.0619</td>
</tr>
<tr>
<td>May 8</td>
<td>1.636</td>
<td>1.6102</td>
<td>-0.0258</td>
</tr>
<tr>
<td>May 10</td>
<td>1.677</td>
<td>1.6243</td>
<td>-0.0527</td>
</tr>
<tr>
<td>May 12</td>
<td>1.71</td>
<td>1.6324</td>
<td>-0.0776</td>
</tr>
</tbody>
</table>

### 5 CONCLUSION

1. Data smooth processing can effectively restrain and weaken the measurement error and reduce the numerical fluctuations of time series, which provides a necessary preparation for neural network numerical prediction.

2. Compared with standard BP neural network, adaptive BP neural network is of faster convergence and higher accuracy so as to be more suitable for engineering.

3. The predicting model based on moving average and adaptive BP neural network can effectively restrain and weaken the measurement error and its method is simple, convergence faster and predictions accurate. Therefore, this method is very suitable for numerical prediction of tunnel vault subsidence values.

### REFERENCES


