Forecast Method of Track Irregularity of Heavy-haul Railway Based on BP Neural Network

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Abstract. The track irregularity is an important factor for the transport safety of heavy-haul railway. Limited by the technique of data mining and analysis, the data obtained by rail inspection vehicles cannot fully identify the status of track irregularity. In this paper, based on the characteristics of track irregularity, the BP neural network is used to predict the geometric irregularity parameters of heavy-haul railway tracks, identify the status of track irregularity, and provide support for the decision-making of maintenance strategy. In order to further verify the accuracy of the BP neural network, the single and double hidden layer networks are established to predict 20 sets of the 7 indicators of track irregularity. According to the prediction results, the mean square errors of the single and double hidden layer networks are 0.064 and 0.051, respectively. The result shows that the multi-hidden layer BP neural network has higher accuracy, which provides a new idea for the research on the prediction model of track irregularity.

1. Introduction
For equipment-intensive heavy-haul railways, more attention is paid to track irregularity assessment technology. However, in practice, manual inspection is generally used, supplemented by rail inspection equipment such as rail inspection vehicles or comprehensive inspection vehicles to dynamically detect geometric irregularities on the track. For example, the Shuohuang Railway in China is equipped with a comprehensive inspection vehicle, but there is still mainly manual detection, supplemented by the comprehensive inspection vehicle. While, the overall disease detection rate of the comprehensive inspection vehicle is only 80% of manual inspection. The reason is that although the comprehensive inspection vehicle can obtain the relevant data of the geometric state of the track, however, the technique of data mining and analysis limits the data obtained to identify the status and causes of track irregularities. In this paper, the BP neural network is used to establish the correlation between track geometric parameters and track structure defects [1-3], to identify the conditions and causes of track irregularities, and thus provide economically feasible track maintenance strategies.

2. Neural Network Model Construction
In the paper, neural network is used as an identification tool to simulate the correlation between track geometric irregularities and track structure defects, and then predict the status of track irregularities. A typical BP neural network is generally composed of 3 layers, namely the input layer, hidden layer (consisting of one or more layers) and output layer, as shown in figure 1.
BP algorithm is also called error back propagation algorithm, there are two main learning stages [4]. The first stage is the forward propagation process stage, the hidden layer calculates the actual output value of each unit by processing the information passing through the input layer. The second stage is the reverse process stage. If the desired output value cannot be obtained, the difference (i.e., the error) between the actual output and the expected output is calculated in a layer-by-layer recursive manner, thereby adjusting the weight by this difference. The basic steps of the BP algorithm are as follows:

Step 1: Set the initial weight to a small random non-zero value.

Step 2: Given a set of input and output samples \( \{u_p, y_p\}_p \), repeat the following processes until the convergence condition is met (\( E_{\text{all}} \leq \varepsilon \)) [5].

1. Calculate the forward process for any sample

   \[
   \begin{align*}
   o_{jp} &= f_1 \left( \sum_{k=1}^{I} w_{kj} u_{ip} \right), j = 1, 2, \cdots J \\
   d_{ip} &= f_2 \left( \sum_{j=1}^{J} w_{ji} o_{jp} \right)
   \end{align*}
   \]

   In the formula, \( I \) and \( J \) are the number of nodes in input layer and hidden layer, \( w_{kj} \) and \( w_{ji} \) are the weights from input layer to hidden layer and hidden layer to output layer, and \( f_1 \) and \( f_2 \) are excitation functions of hidden layer and output layer, respectively. \( o_{jp} \) is output of the \( j \) th node of hidden layer, and \( d_{ip} \) is output of the \( i \) th node of output layer.

2. Calculate the error index \( E_{ip} = \frac{1}{2} \sum_i (d_{ip} - y_{ip})^2 \) and total error index \( E_{\text{all}} = \sum_{p=1}^{P} E_p \), where \( d_p \) is the model output.

3. Calculate the node error of each layer

   \[
   \begin{align*}
   \frac{\partial E_{ip}}{\partial w_{ji}} &= \frac{\partial E_{ip}}{\partial o_{jp}} \cdot f_i \left( \sum_{k=1}^{I} w_{kj} u_{ip} \right) \cdot o_{jp} \\
   \frac{\partial E_{ip}}{\partial w_{kj}} &= \frac{\partial E_{ip}}{\partial o_{jp}} \cdot f_j \left( \sum_{l=1}^{J} w_{jl} o_{lp} \right) \cdot u_{ip}
   \end{align*}
   \]

4. Modify the weight

   \[ w_{ji}(t+1) = w_{ji}(t) - \eta \frac{\partial E_p}{\partial w_{ji}}, \eta > 0 \]

Where \( \eta \) is update step of the weight.

Step 3: Select the step size. In the BP algorithm, the choice of step size \( \eta \) is very important. In order
to solve this problem, the generalized delta rule can be used.

3. Prediction of Track Irregularity Based on BP Neural Network

The data obtained by rail inspection car are the basis for evaluating the status of the track. Generally, evaluation of the track irregularity is made through the processing and analysis of the detection data.

3.1. Evaluation of Track Irregularity

The overall irregularity management of the section includes seven indicators detected by rail inspection car, mainly including gauge, horizontal level, left and right longitudinal levels, left and right orbital directions, and twist of track. The smaller the value of each indicator, the better the track irregularity. The paper analyzes the historical detection data of the track to predict the future by BP neural network.

3.2. Construction of BP Neural Network

- Determination of the number of network layers. According to Kolmogorov theorem, the paper designs a BP neural network with different hidden layers to predict of the track irregularity, to verify the accuracy of the model [6].
- Determination of the neural nodes of the input layer. The number of neural nodes in the input layer depends on the purpose of the network and the type of input data. The neural network is used to forecast the track irregularity level, so the input is the 7 detection indicators that affect the track irregularity. So, the number of neural nodes in the input layer is 7.
- Determination of the neural nodes in the output layer. The neural network in this paper is used to predict the trend of 7 indicators, so the output layer contains 7 nodes.
- Determination of the neural nodes in the hidden layer. The number of hidden layer nodes can be determined by empirical methods. For single hidden layer and double hidden layer BP neural networks, the numbers of nodes can change within a reasonable range, respectively calculate the average prediction accuracy (MSE) of BP neural networks with different numbers of hidden layers for data obtained from the 6 kilometers in Shuohuang railway. The numbers of nodes with the highest accuracy are shown in Figure 2. In the paper, the number of hidden layer nodes of the single hidden layer neural network is 10, and the number of nodes of the first and second layers of the double hidden layer neural network is 12 and 9, respectively.

![Figure 2. Relationship between prediction accuracy and the numbers of hidden nodes](image)

- Determination of excitation (transfer) function. In the BP neural network, there is a functional relationship between the input and output of the hidden layer and the output layer nodes. This function is called the excitation function. The Sigmoid function is a commonly used excitation function. Before using the Sigmoid function, it is necessary to normalize the input and output values of the network in the interval [-1,1].
- Determination of performance function. The performance function is used to evaluate the prediction accuracy of the network. The calculation error is generally chosen as a performance
function. The common performance function is the mean square error (MSE) and the calculation formula of MSE is as follows:

\[ MSE = \frac{1}{N} \sqrt{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \]  

(4)

Where \( N \) is the sample size, \( y_i \) is the observed value of the \( i \) th sample, and \( \hat{y}_i \) is the predicted value of the \( i \) th sample.

- Determination of training function. The training method based on the Levenberg-Marquardt rule not only has a fast convergence speed, but also has the least number of calculations and time spent among all the improved algorithms. Although there is a problem of large memory footprint, the parameters in this paper are not so many, so the training based on the LM rule is still the best choice.

3.3. Analysis of Prediction Accuracy of Neural Network

In order to make the network have higher prediction accuracy, the prediction process must be tested, that is, the historical data is firstly used as the network input and output. The output error between prediction and actual data will be evaluated.

3.3.1. BP neural network accuracy test. Firstly, data of 7 indicators in a certain heavy-haul railway from January 2018 to December 2019 were selected. Then, BP neural networks with different hidden layers are established to predict the track irregularities. The following results are the calculation process and obtained results, and the BP neural network with double hidden layers is taken as an example. The paper uses MATLAB to train and predict the 7 parameters, and analyzes the prediction error at the same time. The variations of gradient and errors in the training process are shown in figure 3. Figures 4 is the training process of the neural network, through continuous learning to approximate the training values of the 7 parameters. As the training process advances, the output of the network gradually approaches the expected values.

![Figure 3. Approximation process of neural network](image3)

![Figure 4. Training process of neural network](image4)

Training based on the existing data, it can be seen from the output results that the results obtained are in line with the actual data, the errors are within the allowable range, so the network can be applied to predict the future data.

3.3.2. Comparison of calculation accuracy of different networks. In order to further verify the accuracy of the BP neural network, this paper compares the results obtained by different networks. The single and double hidden layer networks are used to predict 20 sets of the 7 indicators, respectively. The result is that MSE of the single hidden layer BP neural network is 0.064, while that of double hidden
4. Conclusion

According to the changing characteristics of track irregularity, this paper uses BP neural networks to predict its index parameters, including gauge, horizontal level, left and right longitudinal levels, left and right orbital directions, and twist of track. The results show that the multi-hidden layer BP neural network can predict the track irregularity in each change cycle more accurately. From the prediction results, the double hidden layer BP neural network has higher prediction accuracy than the single hidden layer BP neural network, which shows to a certain extent that as the number of hidden layers increases, it helps to improve the prediction accuracy of the network, while the training time is longer, and it is difficult to determine the network structure and parameters. Through analysis of the data obtained by track inspection vehicles, the dynamic quality of the track irregularities can be mastered. So, the infrastructure management department is able to scientifically guide the track maintenance, effectively evaluate the work quality, and thus achieve the scientific management of the track quality.

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