Study on Vibration Acceleration Prediction Model of Track Inspection Vehicle Based on BP Neural Network

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Abstract. In order to study the mapping relationship between the track irregularity parameters, vehicle running speed and the vehicle vibration acceleration detected by the track inspection vehicle, and to provide better data support for diseases detection of track inspection vehicle and maintenance of rail line, this paper develops a BP (Back Propagation) neural network model that combines the big data analysis technology to predict the vibration acceleration of the track inspection vehicle. The sample data for this model comes from the inspection data of a passenger transport special line in East China. Based on grey relational analysis method, this research preprocesses the correction of mileage deviation for the sample data and analyzes the correlation degree between seven track irregularity parameters and two kinds of vehicle vibration accelerations, the results show that all input layer indicators of the neural network model have different degrees of influence on the output layer indicators. And the predicting results with test data shows that the average accuracy of the whole sample for vertical vibration acceleration and lateral vibration acceleration is 85.75% and 90.25%.

1. Introduction

With the increase of the speed and transporting volume of high-speed trains in China, rail diseases are increasing and the causes are complex. It has become an important basic work to dynamically detect rail status by track inspection vehicles for learning track quality in time and guiding the maintenance and repair of rail lines. Among the detecting items of track inspection vehicles, measurement of vehicle vibration acceleration is one of the important means for monitoring and evaluating rail regularity and passenger comfort. The historic track dynamic detection indicates that the generation of vertical vibration acceleration and lateral vibration acceleration of the vehicle is closely related to the quality of the track geometry and the running speed of the train. Generally, significant track irregularities may cause great vehicle acceleration response and different wavelengths of track irregularities could lead to various vibration accelerations of vehicle under different running speeds [1]. Therefore, analyzing and mining the detection data of track inspection vehicle and studying the mapping relationship between rail geometry status, train running speed and the vibration acceleration of track inspection vehicle is of great significance to detecting rail diseases, guiding line maintenance and improving the train running safety and degree of comfort.

At present, some achievements have been made in predicting the vehicle vibration acceleration referring to track irregularity stimulation and vehicle running speed. Literature [2] analyzes the influence of track irregularity type, amplitude and wavelength on vehicle acceleration based on measured track data. Literature [3] presents a prediction model of RBF (Radial Basis Function) neural network that can predict the changing trend of vibration acceleration based on the vehicle vibration
acceleration data calculated by dynamic simulation software; Literature [4] develops a correlation model between track irregularity and vehicle vibration based on principal component analysis and BP neural network. Literature [5] classifies vehicle inspection data by the magnitude of amplitude and develops a classification prediction model of vehicle vibration acceleration with an improved decision tree algorithm. At present, track inspection vehicle is the main tool for track disease detection, but there are relatively few studies on its vibration acceleration prediction model. And there are still some defects in the detection of vibration acceleration: vibration acceleration is closely related to the running speed of the train. However, the track inspection vehicle usually works under the speed that is lower than the operating speed of high-speed trains, which means the detection values cannot fully represent the actual operating situation of the trains and it could lead to a certain effect on the analysis of vibration acceleration diseases. Meanwhile, the high-speed detection of the whole line is difficult to realize and often leads to errors. And the service life and operating cost of track inspection equipment will be affected to some extent.

This paper proposes a preprocessing method and a correlation analyzing method to detected data of track inspection vehicle for a passenger transport special line in East China. Based on BP neural network algorithm, the study develops a nonlinear mapping model between the rail geometric parameters, running speed and the vibration acceleration of track inspection vehicle, and the predicting accuracy of the model is verified with the actual sample data. Its accuracy meets the engineering standard and could provide more references for inspection and analysis of rail diseases and rail line maintenance.

2. Data preprocessing and Analysis of track inspection vehicle based on grey correlation analysis

2.1. Correction of mileage deviation of track inspection vehicle data

The location on the rail line of detection data is indexed by mileage. But the weak GPS signal, the slides between wheels and rails, malfunction grating encoder and other factors could inevitably lead to the mileage deviation that the detected mileage does not correspond to the standard mileage. The deviation is inconvenient for the on-site maintenance and has a certain impact on the analysis of detection data. So it is necessary to correct mileage deviation for inspected data [6]. In order to provide accurate data support for the development of BP neural network prediction model, this study corrects the mileage deviation of the detected sample data referring to the mileage correction model proposed by the literature [6].

The basic idea of grey correlation analysis is to measure the degree of correlation between factors by geometric relations or the similarity of curves. The more similar the curves change, the greater the correlation degree between the corresponding time series is, conversely, the correlation degree is smaller. Each index of the test data of track inspection vehicle forms the waveform independently and when considering mileage deviation, they are mostly equivalent [7]. This paper selects the K22~K23 km section of a passenger transport special line in East China as the experimental object and takes the sequence of track gauge data detected on 14th February 2017 and 11th March 2017 as the experimental data to carry out the grey correlation analysis as shown in table 1.

| Mileage/m | K |  X₀ |  X₁ |  X₂ |  X₃ |  X₄ |  X₅ |  X₆ |  X₇ |
|----------|---|-----|-----|-----|-----|-----|-----|-----|-----|
| 22029.75 | 1 | 0   | 0.82| 0.76| 0.75| 0.72| 0.7  | 0.66| 0.69|
| 22030.00 | 2 | 0   | 0.9 | 0.82| 0.76| 0.75| 0.72 | 0.7  | 0.66|
| 22030.25 | 3 | 0.06| 1.03| 0.9 | 0.82| 0.76| 0.75 | 0.72 | 0.7  |
| 22030.50 | 4 | 0.17| 1.08| 1.03| 0.9 | 0.82| 0.76 | 0.75 | 0.72 |
| 22030.75 | 5 | 0.17| 1.03| 1.03| 1.03| 0.9 | 0.82 | 0.76 | 0.75 |
| 22031.00 | 6 | 0.14| 0.88| 1.03| 1.03| 1.03| 0.9  | 0.82 | 0.76 |
| 22031.25 | 7 | 0.09| 0.75| 0.88| 1.03| 1.03| 0.9  | 0.82 |     |
In the development of systems, if the trend of the two factors is consistent or synchronization is high, it can be said that there is a high degree of correlation between the two. Table 2 shows that the value of \( \gamma_{106} \) is the biggest, so the similarity between sequence \( X_{106} \) and \( X_0 \) is the best one. It means when moved the compare sequence backward by 106 detecting points, it has the highest correlation with the reference sequence \( X_0 \). Since the distance between each two inspection points of the track inspection vehicle is 0.25m, the mileage data corresponds to the second detection data should be moved backward by 26.5 m as a whole. That is the corrected mileage \( \Delta = 26.5 \) m. The corresponding curves before and after the correction are shown in figure 1 and 2.
The above results indicate that the correction of mileage deviation may improve the quality and availability of detection data. Based on this algorithm, the mileage deviation correction and collation of the detected data from February 2017 to July 2007 were carried out month by month to support the development of BP neural network predicting model.

2.2. Correlation analysis between track irregularity parameters and vibration acceleration

Grey correlation analysis can be used to analyze the degree of correlation between the various factors in the system, so as to judge the main and secondary factors that lead to the development and change of the system, it is a quantitative comparative analysis method for the dynamic development of the system. In order to develop the predicting model effectively and accurately, this paper selects track inspection vehicle data mentioned before as the experimental data to carry out the grey correlation analysis between lateral vibration acceleration and vertical vibration acceleration and track irregularity with the specific steps as follows:

The first step, set the vertical vibration acceleration and lateral vibration acceleration sequences as the reference sequences Y1 and Y2; set track irregularity sequences (track gauge, track alignment, before and after, the level of, superelevation, twist of track, curvature) as compare sequences Yi , the sequence matrix is:

\[ Y_1 = \{ y_1(j) \}, j = 1, 2, \cdots, n; \]  
\[ Y_2 = \{ y_2(j) \}, j = 1, 2, \cdots, n; \]  
\[ Y_i = \{ y_i(j) \}, i \text{ is the sequence number of data, } i = 3, \cdots, 11; j = 1, 2, \cdots, n \]  

The second step, there are different dimension and dimension units between various types of track irregularity parameters. In order to eliminate the dimensional impact between the parameters and to enhance the comparability between the data indicators. This paper normalizes the original data by (0, 1) normalization methodology, the formula is as follows:

\[ X^* = \frac{x - \text{Min}}{\text{Max} - \text{Min}} \]  

Max and Min are the maximum and minimum values in each series.

Substitute the series Y1, Y2 and Yi into equations 1-6, the new normalized matrix is as follows:

\[ Z_1 = \{ z_1(j) \}, j = 1, 2, \cdots, n; \]  
\[ Z_2 = \{ z_2(j) \}, j = 1, 2, \cdots, n; \]  
\[ Z_i = \{ z_i(j) \}, i \text{ is the sequence number of data, } i = 3, \cdots, 11; j = 1, 2, \cdots, n \]
Take the previous example of the grey correlation analysis, substitute the sequence matrix $Z_1$ and $Z_2$ and $Z_i$ into equation 1-1 and 1-2, take identification coefficient $\rho = 0.5$, the grey correlation analysis results are shown in Table 3 and Table 4.

**Table 3. Grey correlation Analysis of Vertical Vibration acceleration and track irregularity ( $\rho =0.5$)**

| Longitudinal irregularity | Track alignment | Track gauge | Horizontal irregularity | Super elevation | Curvature | Track twist |
|---------------------------|-----------------|-------------|-------------------------|----------------|-----------|------------|
| Left                      | Right           | Left        | Right                   |                |           |            |
| 0.87671                   | 0.89739         | 0.87597     | 0.87266                 | 0.78578        | 0.85880   | 0.69151    | 0.69037 | 0.82515 |

**Table 4. Grey correlation analysis of horizontal vibration acceleration and rail irregularity ( $\rho =0.5$)**

| Longitudinal irregularity | Track alignment | Track gauge | Horizontal irregularity | Super elevation | Curvature | Track twist |
|---------------------------|-----------------|-------------|-------------------------|----------------|-----------|------------|
| Left                      | Right           | Left        | Right                   |                |           |            |
| 0.87675                   | 0.89739         | 0.87597     | 0.87274                 | 0.79599        | 0.86005   | 0.70544    | 0.70862 | 0.81789 |

In the development of BP neural network, the reason why the track irregularity parameters are selected as the input index of the input layer is that various track irregularities have different degrees of influence on the vibration acceleration of track inspection vehicles. Longitudinal (high and low) irregularity and track alignment diseases can increase the impact dynamics of passing trains, causing shaking and vibration of vehicles, it could result to the excitation frequency which has a significant effect on the vibration acceleration. From Table 3 and Table 4, it can be seen that the correlation coefficients of experimental rail line between either the longitudinal (high and low) irregularity or track alignment and the vibration acceleration are all above 0.87. Track twists and horizontal irregularity can cause tilting and rolling vibration of the vehicle, resulting in changes in the wheel-rail interaction force, which have a certain impact on the vibration acceleration. The correlation coefficients of these two parameters and vibration acceleration in the experimental rail line are all above 0.81. Significant deviation of track gauge, superelevation, and curvature can cause vehicle vibration and affect the operating safety of the trains. The correlation coefficients between each of the three parameters of the experimental rail line and the vibration acceleration are all above 0.69.

3. **BP neural network prediction model based on inspection data of track inspection vehicle**

BP neural network has excellent ability of multidimensional function mapping. This algorithm does not need to determine the mathematical equation of the mapping relationship between input and output in advance, only through the training of the sample data and learning some rules can obtain the result closest to the expected output value when the input value is given. This study collates 4000 groups of sample data and 500 groups of test data based on the existing inspected data. They are used for training the vibration acceleration prediction model and for analyzing its errors.

3.1. **Development of BP neural network model**

In this paper, the design of BP neural network structure is realized by toolbox function of MATLAB platform and by using single hidden layer neural network structure to develop the prediction network model of the vehicle vibration acceleration. The input layer is of 9 parameters of track irregularity and the running speed of track inspection vehicle, that is, the input layer contains 10 neurons; the number of the hidden layer neurons is determined to be 15 after debugging analysis and S-type transfer function (Sigmoid) is used. The output layer adopts linear transfer function (Purelin) and two output neural nodes are set to output vertical and lateral vibration acceleration respectively. The complete neural network is designed as shown in figure 3. Through trial calculations, the learning rate is set as 0.5; the error is set as $0.0001g$ and the maximum training step number is 1000.
3.2. The training and error analysis of prediction model
In this section, the selected sample data is edited to form a matrix data text, it is input into the designed BP neural network for training after the normalization. After the training of BP neural network, the average relative error of the sample can reach to 0.000085g, it is less than the expected error of 0.0001g. After calculated the test sample on the trained network, the prediction data of 0-25m range from K66 km point is randomly selected to compare with expected results, as shown in figure 4 and figure 5:

Figure 3. Debugging finished network structure diagram of BP neural network

Figures 4 and 5 indicate that the acceleration values of the vehicle vibration predicted by the neural network developed in this paper are close to or equal to the measured values. The BP neural network can well simulate the mapping relationship between track irregularity parameters, speed and vehicle vibration acceleration, so as to achieve a good prediction effect. Combined with the analysis of 500 groups of test samples, it is known that the maximum absolute error of vertical vibration acceleration prediction is 0.010 g, the average accuracy of the sample in whole is 85.75%; the maximum absolute error of the lateral vibration acceleration prediction is 0.006 g, and the average accuracy of the sample in whole is 90.25% (accuracy = 1 - relative error).

4. Conclusions
In order to develop and apply a prediction model of vibration acceleration for track inspection vehicle based on track irregularity parameters and running speed, this paper selects and analyzes the track inspection vehicle data from a passenger transport special line in East China. The main works are summarized as follows:

(1) Using the grey relational algorithm correction model proposed in the existing research, the correction of the mileage deviation existing in the track inspection vehicle data was corrected and preprocessed.

(2) Based on the grey correlation analysis method, the correlation degree between the selected input layer indicators and output layer indicators of BP neural network was analyzed. Various track irregularity parameters (input layer) have a good correlation with vertical and lateral vibration accelerations (output layers) of the track inspection vehicle, and are suitable to be selected as the input layer variables of the BP neural network.

(3) Based on the detection data of track inspection vehicles, this study trained a BP neural network model that can predict vehicle vibration acceleration with track irregularity parameters and running speed. Through the computation with test data, the average accuracy of the predicted vertical vibration acceleration and the lateral vibration acceleration are respectively 85.75% and 90.25%. It proves that this model has good applicability and reliability for engineering application.

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