Prediction Method of Heavy Load Wheel/Rail Wear Mechanical Properties Based on GA-BP Hybrid Algorithm

Xiao Xue[1], Yangbing Zheng[2,3] and Xin Wang[4,*]

[1]*School of Information Engineering, Nanyang Institute of Technology, Nanyang 473004, Henan, China*
[2]*College of Mechanical and Electronic Engineering, Nanyang Normal University, Nanyang 473061, Henan, China*
[3]*Qinghai Wandong Ecological Environment Development Co.LTD, Geermu 816000, Qinghai, China*
[4]*Henan Minghui Construction Group Co.LTD, Zhengzhou 450000, Henan, China*
E-mail: 86507472@qq.com
[*]*Corresponding Author*

Received 29 September 2022; Accepted 24 October 2022;
Publication 26 November 2022

Abstract

Due to its large axle load and high-density operation mode, heavy haul transportation has greatly improved the cargo transportation capacity, and is receiving unprecedented attention from all countries in the world. Since the development of heavy haul freight transport in China, wheel rail wear has been paid much attention, especially the use of heavy axle load locomotives on upgraded heavy haul lines, which makes reducing wheel rail wear and damage become a technical problem to be solved urgently. Considering that there are too many mechanical parameters involved in the prediction of heavy load wheel rail wear mechanical properties, the prediction accuracy is reduced. Therefore, this paper proposes a method based on GA-BP hybrid algorithm to predict the mechanical properties of heavy load wheel/rail wear.

European Journal of Computational Mechanics, Vol. 31_3, 409–432.
doi: 10.13052/ejcm2642-2085.3134

Hertz contact theory is used to simplify the wheel rail contact relationship, and the wheel rail contact model is established. According to the wheel/rail contact model, the expressions of heavy load wheel/rail in the case of vertical, horizontal, direction and gauge irregularity are analyzed, and based on this, a mechanical model of heavy load wheel/rail wear is established. In order to solve the problems of slow convergence speed and easy to fall into local optimum of BP neural network in the prediction of heavy load wheel/rail wear mechanical properties, the global convergence of genetic algorithm is used to optimize the BP network. According to the obtained mechanical parameters of heavy load wheel/rail wear, the mechanical parameters are input into the optimized model, and the relevant prediction results are output. So far, the research on the prediction method of heavy load wheel/rail wear mechanical properties based on GA-BP hybrid algorithm has been realized. The experiment is designed from three aspects of wear degree, hardness and tensile strength, and compared with the measured value, reference [4] method, reference [5] method and reference [6] method to verify the effectiveness of the proposed method. The experimental results show that the predicted results of wear degree, hardness and tensile strength by this method are closer to the measured results. It is proved that the proposed method has higher prediction accuracy and better practical application effect.

Keywords: GA-BP hybrid algorithm, heavy duty wheel/rail, wear, mechanical property prediction, wheel/rail contact model, mechanical model of rail wear.

1 Introduction

Since the beginning of the 21st century, the railway has made constant efforts to tackle key problems in rolling stock, high-speed railway, speed increase of existing lines, plateau railway, heavy haul transportation and other technologies for stepping into the world's advanced ranks, ushering in a major breakthrough in modernization. The transportation efficiency has ranked first in the world, making important contributions to economic and social development. Adhering to integrated innovation, original innovation, introduction, digestion, absorption and re innovation, China's railways have made remarkable achievements in promoting high-speed railways. While speed creates miracles, China's heavy haul transportation is also constantly breaking new records. The containerization, heavy loading and logistics of freight transport are the general trend of the development of railway freight transport in the world today [1]. In the 1920s, heavy haul railway transportation first appeared in the United States. With the rapid development of heavy haul railway, the axle load of freight cars is gradually increasing, the number of train formation is gradually increasing, and the number of locomotives and vehicles is gradually decreasing, which greatly reduces the energy consumption required by locomotive traction, reduces the maintenance and repair of vehicles, and increases the overall transportation turnover efficiency while greatly reducing the economic cost and time cost. In today's world, heavy railway is an important component and direction of railway freight development [2]. When transporting large goods, heavy haul railway transportation has the characteristics of safety, environmental protection and timeliness. It is of great significance to ensure the energy supply and promote the balanced and rapid development of multi regional economies. With the gradual increase of the running speed and axle load of heavy haul railway trains, the rail damage is becoming increasingly serious, which is mainly manifested in side wear, peeling off blocks, rail head widening and corrugation [3]. This brings a great burden to the maintenance work, and brings huge economic losses. At the same time, the increase of axle load makes the problems of wheel wear, tread peeling, cracks, scratches and other diseases increasingly prominent, which seriously affects the safety of heavy haul railway transportation and hinders the vigorous development of heavy haul railway industry.

For the important research topic of heavy load wheel/rail wear prediction, reference [4] shows that according to the Archard wear strength model, the volume wear is related to the wear work, mainly due to the creep and positive pressure between wheels and rails. In this paper, based on the UM software, the relationship between wheel/rail contact creep, lateral displacement and vehicle rail system parameters is established by the multivariable parallel discrete calculation method, and the wheel/rail wear prediction model under the influence of multi parameters is established. Reference [5] aimed at the problem of high replacement cost of brake shoes caused by serious wear of brake shoe of railway freight car, based on the depth belief network (DBN), fitted the distribution law of brake shoes wear of railway heavy haul freight car, and realized the prediction of brake shoe wear thickness at different positions of railway heavy haul freight car. In reference [6], in order to accurately obtain the wear changes of the wheel tread of metro vehicles with the train mileage, the grey metabolism model, the quadratic exponential smoothing model and the unitary linear regression model were selected as the single prediction model, and the optimal non negative variable weight combination prediction model for the wear change trend of the wheel tread of metro vehicles was established with the minimum absolute value of the combined prediction error at the sample point as the optimal criterion. Reference [7] designed the wear prediction model of pantograph sliding plate of train power supply system. Linear support vector regression, least squares support vector regression and optimized least squares support vector return method are used to train and fit the pantograph sliding plate data obtained by the detection system, and the trained model is used to predict the sliding plate wear. In reference [8], in order to accurately predict the tread wear during train emergency braking, a thermal mechanical coupling finite element model of the tread braking process was established based on the finite element software ABAQUS. Considering the impact of brake temperature rise on the mechanical performance, hardness and friction coefficient of wheel tread, the temperature distribution The hardness distribution and contact stress distribution, and the wheel/rail contact spot shape and the relative slip distribution of the wheel/rail creep zone during the emergency braking process were obtained by using the wheel/rail dynamics software UM. On this basis, the tread wear depth after the single emergency braking was quantitatively predicted with the Archard wear model. Reference [9] calculated the dissipated energy due to friction to assess material loss and determine the shape of the contact surface during wear evolution. The contact problem is solved numerically by finite element method, operator splitting method and semi smooth Newton method. The contact surface stress and temperature, surface shape and wear depth are analyzed. Reference [10] reexamined the causes of wheel wear in wheel sets. This method points out that theoretical mechanics can be used to verify the linear velocity change of the wheel in the wheel set at the rail joint, which leads to the lateral drift of the wheel and the additional strain on the rim, which is one of the main reasons for different types of wear. At the same time, the method found that the vibration generated when the wheelset moved at the joint had a negative impact on the wear strength. Reference [11] tested the friction and wear of railway transportation used for wheel rail system when sliding on Amsler friction testing machine. The relationship between wheel rail wear rate and wheel rail contact temperature is obtained by this method.

However, there is a problem of low prediction accuracy when the above methods are applied to the prediction of heavy load wheel/rail wear mechanical properties. Therefore, in order to optimize the prediction effect of mechanical properties of heavy-duty wheel/rail models, a method based on GA-BP hybrid algorithm for predicting the mechanical properties of heavy-duty wheel/rail wear is proposed. In this paper, BP network and genetic algorithm (GA) are combined to optimize the initial weights and thresholds of BP network by using the global convergence of genetic algorithm. Then the BP network adjusts and searches. Finally, the trained network is applied to the prediction of heavy load wheel/rail wear mechanical properties, and the effectiveness of this method is verified through experiments.

2 Design of Prediction Method for Mechanical Properties of Heavy Load Wheel/Rail Wear

2.1 Mechanical Model of Heavy Load Wheel/Rail Wear

Wheel/rail contact refers to the contact between high-speed vehicle wheel sets and ballastless track rails. The forward movement of rolling stock is realized by rolling the wheel set on the rail [9]. In order to maintain good dynamic performance when the vehicle is running, and to transmit the force of the wheel set on the rail well, it is necessary to make a matching relationship between the wheel tread and the rail profile [10, 11].

In this paper, Hertz contact theory is used to simplify the wheel/rail contact relationship. Hertz contact theory is shown in the following formula:

$$p(t) = \left[\frac{1}{G}\delta Z(t)\right]^{3/2} \tag{1}$$

Where, G is the contact constant [12], and $\delta Z(t)$ is the compression between wheel and rail.

For tapered tread wheels, there are:

$$G = R \times 10^{-8} \ (m/N^3) \tag{2}$$

Where, R represents the wheel radius.

For worn tread wheels, there are:

$$G = R \times 10^{-8} \ (m/N^3) \tag{3}$$

The following formula is valid:

$$\delta Z(t) = Z_{wj}(t) - Z_r(x_{rj}, t) \tag{4}$$

In the formula, $Z_{wj}(t)$ represents the displacement of j wheelsets at t hours, and $Z_r(x_{rj}, t)$ represents the displacement of rails under j wheelsets at t hours [13].

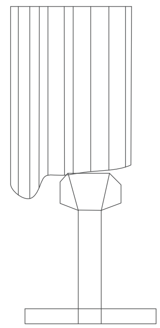


Figure 1 Wheel/rail contact model.

When $\delta Z(t) < 0$, it means that the wheel is derailed, and the wheel/rail force is $p(t) = 0$. When the rail surface is not smooth, the calculation formula of wheel/rail force is as follows:

$$p(t) = Z_{wj}(t) - (Z_r(x_{rj}, t)Z_0(t)) \tag{5}$$

According to the wheel/rail force calculated by the above formula, the wheel/rail contact model established is shown in Figure 1.

Since the rail is not in an ideal straight state, the height, left and right of the two rails have deviations from the ideal state. The deviation of their geometric parameters is called track irregularity [14, 15]. There are blue types of irregularities: deterministic functions, such as sine, step, bevel gear, etc; Random function, generally PSD; Given the excitation, the data will be measured during actual operation on site. The combined effects of rail wear and damage, uneven sleeper spacing, uneven grading and strength of track bed, and dirt on the actual line constitute the random characteristics.

The excitation function in the time domain, and the main source of vehicle vibration. The Research and Experiment Committee of the International Railway Union pointed out that Germany's high-speed track spectrum is the most representative. The German high speed spectrum consists. For ballastless track, German low interference spectrum is selected for calculation. The expressions of vertical, horizontal, direction and gauge irregularities of German high-speed track spectrum are as follows:

(1) The expression of direction irregularity is as follows:

$$S_A(\Omega) = \frac{A_A \cdot \Omega_C^2}{(\Omega^2 + \Omega_R^2)(\Omega^2 + \Omega_C^2)} \tag{6}$$

(2) The expression of height irregularity is as follows [16]:

$$S_V(\Omega) = \frac{A_V \cdot \Omega_C^2}{(\Omega^2 + \Omega_R^2)(\Omega^2 + \Omega_C^2)} \tag{7}$$

(3) The expression of horizontal irregularity is as follows:

$$S_C(\Omega) = \frac{(A_V/b^2) \cdot \Omega_C^2 \cdot \Omega^2}{(\Omega^2 + \Omega_R^2)(\Omega^2 + \Omega_C^2)(\Omega^2 + \Omega_S)} \tag{8}$$

(4) The power spectral density of gauge irregularities has the same expression as that of horizontal irregularities:

$$S_C(\Omega) = \frac{A_G \cdot \Omega_C^2 \cdot \Omega^2}{(\Omega^2 + \Omega_R^2)(\Omega^2 + \Omega_C^2)(\Omega^2 + \Omega_S)} \tag{9}$$

$S_A(\Omega)$, $S_V(\Omega)$, $S_C(\Omega)$ and $S_G(\Omega)$ represent the power spectral density of direction, height, level and gauge irregularities. A_V, A_A, A_G represents different roughness constants, Ω represents spatial frequency, *b* represents left and right rolling circle radius distance, and Ω_C, Ω_R, Ω_S represent different truncation frequencies.

The mechanical model of heavy load wheel/rail wear is as follows:

$$s(t) = \left[\frac{1}{G}\delta Z(t)\right]^{\frac{3}{2}} + \frac{S_A(\Omega) + S_V(\Omega) + S_C(\Omega) + S_G(\Omega)}{4} \tag{10}$$

2.2 Prediction of Mechanical Properties Based on GA-BP Hybrid Algorithm

Genetic Algorithm (GA) and Back Propagation (BP) are the most widely used intelligent optimization algorithms in geophysical exploration. GA algorithm can solve the optimal value in a random way in the sense of probability. Due to its relatively simple operation and intuitive and effective problem solving, it has been applied in many fields. But sometimes its solution effect is not the most effective solution of the target problem, and it is not more efficient than the knowledge-based heuristic algorithm; In contrast, gradient descent method, Lagrangian multiplier method, neural network and other optimization algorithms have strong local mapping ability, and the operation efficiency of heuristic algorithms containing problems is also high. Therefore, the starting point of the hybrid algorithm strategy is to integrate other optimization algorithm ideas in the GA algorithm search process to form a nonlinear hybrid global optimization algorithm that can improve the solution quality and operation efficiency. Therefore, this paper uses GA-BP hybrid algorithm to predict the mechanical properties of heavy load wheel/rail wear, which can improve the prediction quality and efficiency.

The idea of GA-BP hybrid algorithm is to improve and optimize the parameters and network topology of the neural network by using the global search ability and parallel processing information mode of the GA algorithm based on the random search mechanism, which overcomes the defects of simple BP algorithm.

Assuming that the output of each layer of the neural network is expressed in a matrix, $u_1, u_2, \ldots, u_n$ represents the previous layer, $w_1, w_2, \ldots, w_n$ represents the weight value of the current layer, $b_1, b_2, \ldots, b_n$ represents the threshold value of the current layer, and $y_1, y_2, \ldots, y_n$ represents the output value of the current layer, then there are:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} \tag{11}$$

Its matrix form is expressed as:

$$Y = WP + B \tag{12}$$

Suppose the neural network has three layers: input layer, hidden layer and output layer. The input layer data is U, the hidden layer output data is $A1$, the weight and threshold are $W1$ and $B1$, the output layer data is $A2$, and the weight and threshold are $W2$ and $B2$, then the network output layer data:

$$A2 = W2A1 + B2 = W2(W1U + B1) + B2 \tag{13}$$

Adjusting the weights, thresholds and the number of hidden layer nodes can make the predicted output value of the neural network more close to the ideal output value.

Based on the above analysis, the specific analysis of GA algorithm optimizing BP neural network is as follows:

(1) Determine chromosome coding scheme

As the basis of GA algorithm, the effective determination of chromosome coding scheme can reflect the advantages of GA algorithm. Real number coding is often used in practical problems. The code string is mainly composed of the following four parts: the number of hidden layer nodes, the connection weight between layers, the hidden layer unit threshold and the output layer unit threshold.

(2) Population initialization

11 chromosomes were randomly generated. GA operation is to use replication, crossover, mutation and other operators to conduct effective information exchange among individuals within a population. The key technology is to set the initial population size and control the population size in the process of genetic evolution.

(3) Fitness function setting

GA algorithm is usually not affected by external information when running, but uses the internal force, namely fitness function value, as the basis of genetic operation to evaluate the merits of individuals. The definition domain of fitness function is an arbitrary set, and it is not subject to the constraints of continuity and differentiability. The only constraint is that the input can calculate comparable non negative results. The fitness value formula of the i-th individual after ranking is as follows:

$$F(x) = \begin{cases} f(x) - F(x), & \mathit{if}\ g_j(x) \geq 0\ \forall j = 1, 2, \ldots, N \\ f\max + \sum_{j=1}^{m} (gj(x)) - \overline{F(x)}, & \mathit{other} \end{cases} \tag{14}$$

Where, $f(x)$ is the individual objective function value, $f\max$ is the worst individual fitness value, $\overline{F(x)}$ is the average fitness value of the previous generation, and $g_j(x)$ is the output value of node j. The setting of this fitness function not only reflects the population difference between adjacent generations, but also is closely related to the individual objective function, which is more intuitive and less than the general reciprocal of the error square in terms of time complexity.

(4) Genetic operator design

In this paper, the optimal selection strategy is used as the selection operator design method in GA.

The crossover operation plays a key role in the global search of GA optimization, and belongs to the core genetic operation. Set x_1^t, x_2^t as the post crossover gene value, x_1, x_2 as the pre crossover gene value, and a as the real number randomly generated between [0,1]. The crossover operator used in this paper is shown in the following formula:

$$x_1' = (1-a)x_1x_2 \tag{15}$$

$$x_2' = a(x_2 + x_1) \tag{16}$$

The mutation operator selects the mutation point and randomly generates the real value. In this paper, the method of randomly selecting variation points is used to randomly select variation values in the interval. Therefore, the variation value interval of individual X_1's locus x_1 is shown in the following formula:

$$x_1 = x^{\min} + \left| \frac{x^{\min} \times p_m \times f_i}{f\max} \right| \tag{17}$$

$$x_2 = x^{\max} + \left| \frac{x^{\max} \times p_m \times f_i}{f\max} \right| \tag{18}$$

Where, $x^{\min}$ and $x^{\max}$ are the minimum and maximum values of variability, f_i are the objective function values of individual X_i, $f_{\max}$ are the maximum objective function values, and p_m are the variability.

(5) Adaptive crossover rate and mutation rate

In order to avoid premature convergence or slow evolution of the algorithm due to improper selection of crossover rate and mutation rate, this paper proposes an improved adaptive genetic algorithm (IADA), as follows:

$$p_c = \begin{cases} p_{c\min} + \left(p_{c\max} - p_{c\min} \times e^{-10(\frac{f_{avg}-f}{f_{\max}})} \right) & f' \geq f_{avg} \\ p_{c\max} f' < f_{avg} \end{cases} \tag{19}$$

$$p_m = \begin{cases} p_{m\min} + \left(p_{m\max} - p_{m\min} \times e^{-10(\frac{f_{avg}-f}{f_{\max}})} \right) & f \geq f_{avg} \\ p_{m\max} f < f_{avg} \end{cases} \tag{20}$$

In the formula, $p_{c\min}$ and $p_{c\max}$ represent the lower limit and upper limit, $p_{m\min}$ and $p_{m\max}$ represent the lower limit and upper limit, $f_{\max}$ represent

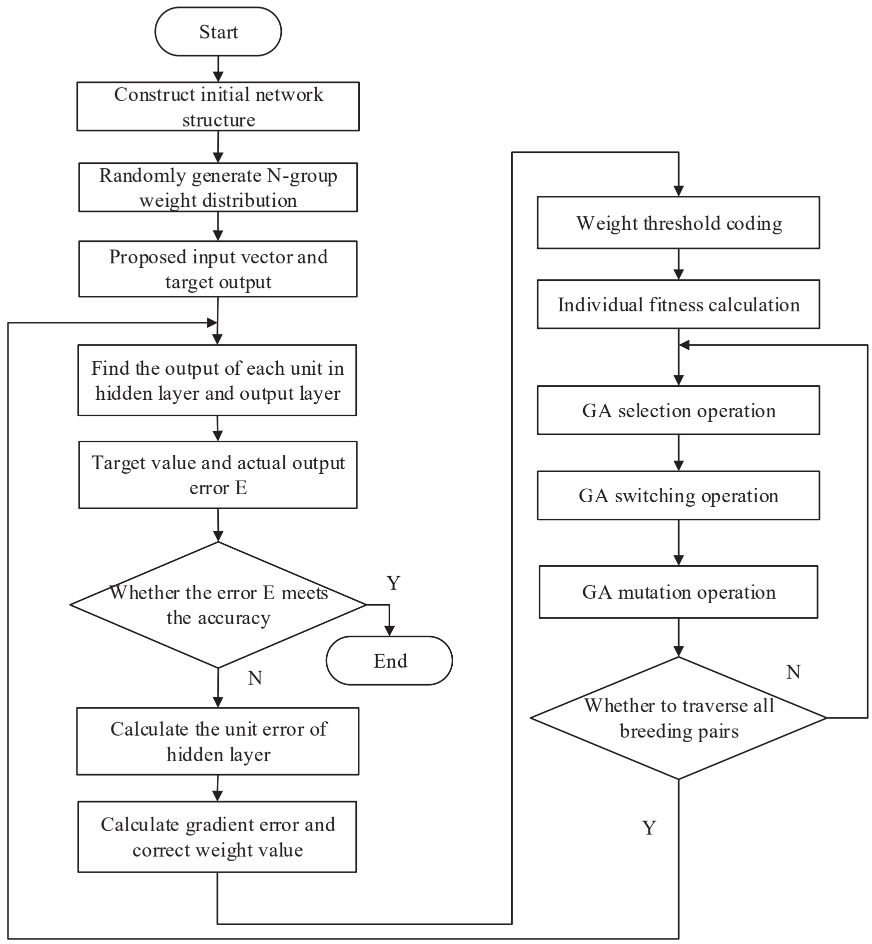


Figure 2 Prediction process of heavy load wheel/rail wear mechanical properties.

the maximum fitness of the population, f_{avg} represent the average fitness, f' represent the larger, and f represent the fitness function.

The prediction process of heavy load wheel/rail wear mechanical properties based on GA-BP hybrid algorithm is shown in Figure 2.

To sum up, the specific steps for predicting the mechanical properties of heavy load wheel/rail wear based on the GA-BP hybrid algorithm are as follows:

(1) Based on the mechanical parameters of heavy load wheel/rail wear, combined with the construction characteristics of the optimization problem,

the input layer, hidden layer and output layer of the neural network are constructed, and N groups of connection weights and threshold distributions are randomly generated as the initial population of the GA algorithm.

(2) The data standardization method is used to provide normalized learning samples for neural networks, including input samples and target outputs.
(3) Calculate the corresponding systematic error of the initial population of the group, and judge whether it is less than or equal to the network preset threshold. Stop iteration if conditions are met; Otherwise, the gradient error is calculated and the weight threshold distribution is corrected.
(4) Determine the weight threshold coding method, and select the fitness function shown in formula (14) to calculate the individual fitness value.
(5) Carry out a series of GA algorithm operations to generate a new population, calculate repeatedly within the set number of iteration termination times until all breeding individuals are traversed, so as to improve the population performance.
(6) The optimized BP neural network is used to predict the mechanical properties of heavy load wheel/rail wear, and the relevant prediction results are obtained.

3 Experimental Design

The experimental equipment is MM-200 heavy load wheel/rail testing machine. The MM-200 heavy load wheel/rail tester can be used to test the wear resistance of many metal materials and non-metallic materials under rolling friction, sliding friction, rolling sliding composite friction and intermittent contact friction. It can also measure the friction coefficient of the sample and determine the friction and wear mechanism of the sample. At the same time, it can also simulate the dry friction, wet friction and abrasive wear of samples under different experimental parameters. The slip rate between samples can be achieved by setting experimental parameters through rolling friction experiment. MM-200 heavy load wheel/rail testing machine is shown in Figure 3.

The testing machine can work normally under the following conditions:

(1) Within the range of 10°C – 35°C at room temperature;
(2) Environment with humidity no more than 70%;
(3) There is no other medium pollution and electromagnetic interference around the instrument;

Figure 3 MM-200 heavy load wheel/rail testing machine.

(4) The power supply voltage of the instrument shall be stable at the rated voltage level, and the operating frequency shall also be stable at the rated frequency level;
(5) Install horizontally on a stable foundation.

The experimental process of predicting the mechanical properties of heavy load wheel/rail wear is divided into four parts: preparation before the experiment, process control during the experiment, post-processing of the experiment, and analysis of the experimental results.

3.1 Preparation Before Experiment

Preparation before experiment The main preparations before experiment are:

(1) According to the theory of Hertz simulation criterion, conduct trial installation and operation for the finished sample, and check whether the size of the sample meets the experimental requirements and equipment requirements. Qualified samples shall be marked and stored in culture dishes; Unqualified samples shall be reprocessed.

(2) Take out the qualified sample in the culture dish. Put it into a small beaker with acetone, and then clean the surface of the sample with an ultrasonic cleaning instrument to remove the pollutants on the surface of the sample.

(3) FM-300 digital microhardness tester was used to measure the hardness of wheel/rail samples before heavy load wheel/rail wear mechanical properties prediction experiment. Ten hardness values are measured for each sample, and then the average value is calculated as the hardness value before the heavy load wheel/rail wear mechanical property prediction experiment.

The microhardness tester used in this experiment is a Japanese Hengyi FM-300 digital microhardness tester, equipped with SVDM3 hardness

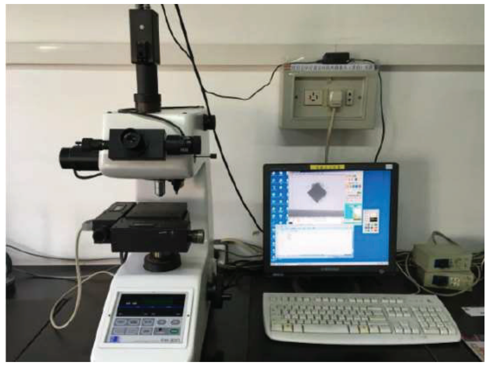


Figure 4 Digital microhardness tester.

Figure 5 AR2140 precision electronic balance.

measurement software system. If there is no special instruction, the load selected in this experiment is 200 g when testing the hardness of pearlite structure. The applied load is 200 g and the holding time is 10 s. The digital microhardness tester is shown in Figure 4.

(4) The AR2140 electronic balance with a sensitivity of 0.1 mg is used to weigh the wheel/rail sample before the experiment. Each sample is weighed three times in a row, and the error of each measurement is less than 1 mg. When the display number of the instrument is stable, record the data and calculate the average value. AR2140 precision electronic balance is shown in Figure 5.

The AR2140 precision electronic balance can accurately measure the weight of the sample before and after the experiment, and then obtain the wear amount of the simulated sample after subtraction. Its main parameters are as follows:

The maximum weight is 210 g; The accuracy is 0.0001 g (0.1 mg); The size of the weighing pan is 90 mm; The stabilization time is 4 s; The environmental requirement is 10°C∼30°C; The power supply is AC power.

The main features are as follows:

The weighing range of the instrument is 0 g∼210 g, and the accurate value can reach 0.0001 g; Piece weighing mode; Multiple weighing units; Built in lower scale hook; Standard RS232 communication interface; The plastic protective cover of the rack is standard.

(5) Install the rail sample and wheel sample on the upper and lower sample shafts of the heavy load wheel/rail wear mechanical property prediction test machine respectively, and check whether the wheel/rail sample surface is aligned and contacted.

(6) Start the power supply of the testing machine. After debugging the parameters of the testing equipment, apply the test load and confirm that there is no error. Click the "Start" button to start the test. After starting the experiment, timely adjust whether the applied load is stable, and observe and check whether the experimental equipment operates normally.

The tensile testing machine used in this experiment is a WE-300 hydraulic tensile testing machine manufactured by Tianshui Experimental Machine Factory. The tensile tests were carried out at room temperature. The round section proportional sample is adopted Φ Take 3 identical samples with the specification of 10 mm, and take the average of the results. The hydraulic tensile testing machine is shown in Figure 6.

Figure 6 Hydraulic tensile testing machine.

Figure 7 Pendulum impact testing machine.

The impact testing machine used in this experiment is a pendulum impact testing machine, the model is JBN-300B, and the maximum energy is 300 J. The wheel/rail sample shall refer to the relevant standards for wheel/rail inspection. The impact sample shall be U-notch sample with a specification of 55 mm $\times$ 10 mm $\times$ 10 mm. When the impact toughness is tested in this experiment, the experimental temperature is room temperature. The pendulum impact test machine is shown in Figure 7.

3.2 Experimental Process

In the process of heavy load wheel/rail wear mechanical property prediction experiment, there are mainly wire cutting and finishing grinding of simulated samples, debugging of experimental equipment, normal experiment and treatment of wheel/rail sample wear scar surface after the experiment. During the heavy load wheel/rail wear mechanical property prediction experiment, observe the vibration of the upper and lower wheels of the test machine at all times. Once it is found that the test machine vibrates severely up and down due to the misalignment of the sample, the operation of the instrument should be stopped immediately to avoid damage to the test instrument.

3.3 Post Experiment Treatment

Main work after the experiment:

(1) After the experiment, record and save the experimental data. After manual unloading, take down the wheel/rail sample and put it into the culture dish. Then use acetone ultrasonic wave to clean the surface of the sample. After it is dried, use the AR2140 electronic balance with a

sensitivity of 0.1 mg to weigh the weight of the sample after friction and wear. Each sample is weighed three times repeatedly. When the instrument displays a stable number, record the measured data, and finally calculate the average value. The experimental data shall be sorted out and summarized in a timely manner, and the experience and problems in the experiment shall be summarized.

(2) Before and after each test, use a digital camera to take a macro photo of the wear surface of the simulated wheel/rail sample, and record the test time of the wheel/rail sample and the corresponding wear surface of the sample.

(3) In order to achieve the purpose of the experiment and the requirements of the experimental equipment, the wheel/rail sample is processed into a suitable shape and size, cleaned with acetone ultrasonic, and stored in a petri dish after drying for relevant experimental analysis.

3.4 Analysis of Experimental Results

The method of reference [4], the method of reference [5], the method of reference [6] and this paper have predicted the wheel rail wear, and compared with the measured value. The results are shown in Figure 8.

From Figure 8 shows that the predicted results and measured values of different methods show a rising trend. When the experimental time is 90 s, the predicted results and measured values of different methods reach the maximum. Among them, the maximum value of the abrasion prediction

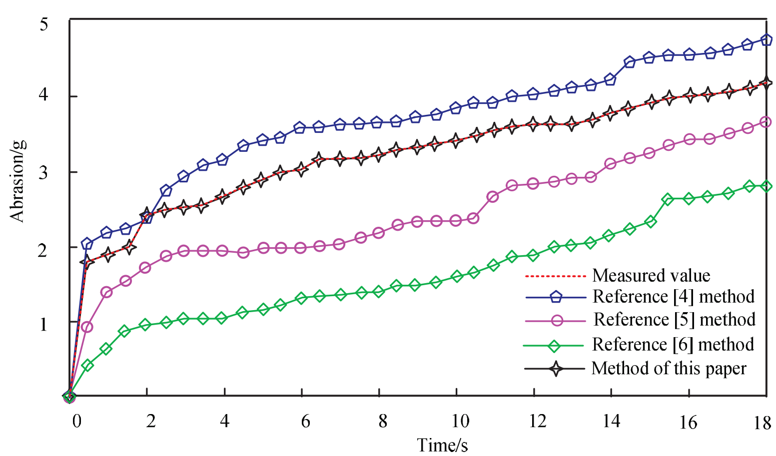
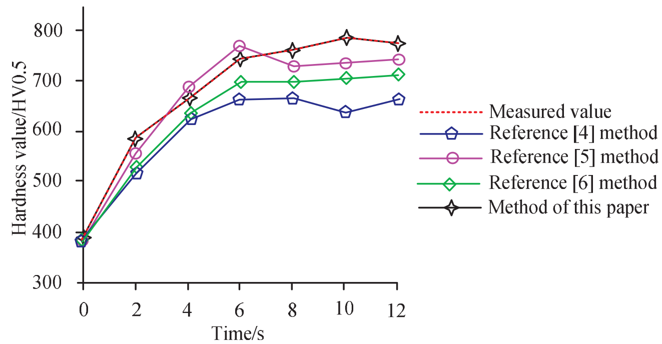
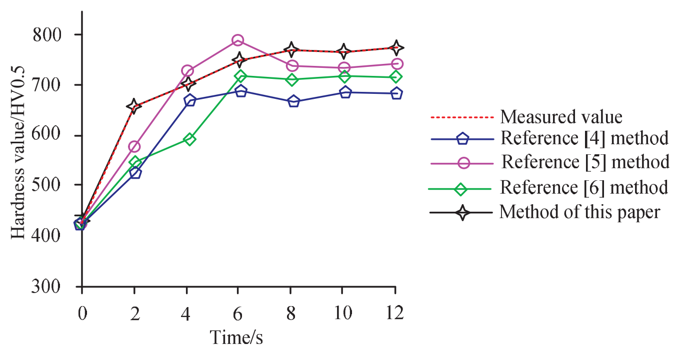


Figure 8 Comparison results of abrasion.



(a) Rail



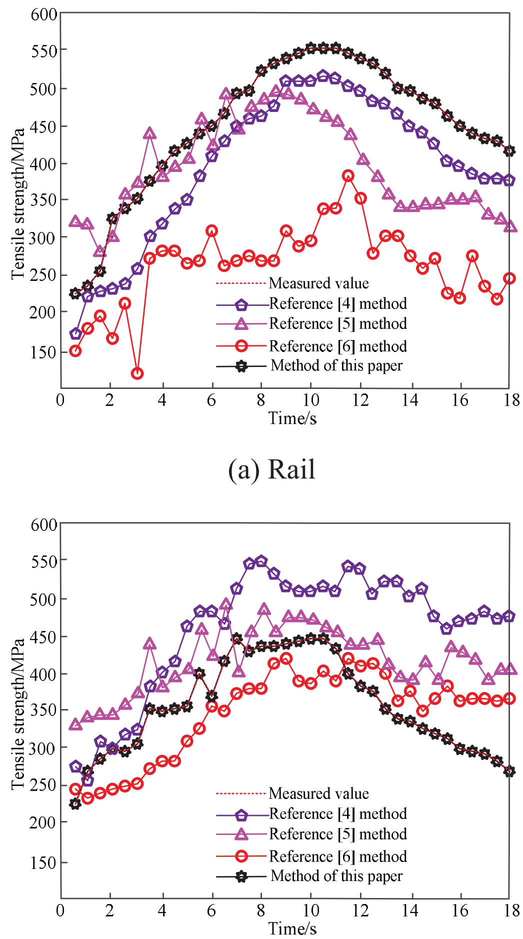
(b) Wheels

Figure 9 Prediction results of wheel/rail hardness values.

result of reference [4] method is 4.7 g, the maximum value of the abrasion prediction result of reference [5] method is 3.5 g, the maximum value of the abrasion prediction result of reference [6] method is 2.7 g, and the maximum value of the abrasion prediction result of this method is 4.1 g, which is consistent with the measured value, indicating that this method is more accurate for the abrasion prediction result.

The method of reference [4], the method of reference [5], the method of reference [6] and the method in this paper predict the wheel/rail hardness values and the actual results are shown in Figure 9.

The analysis of wheel/rail hardness changes shows that under heavy load, the hardness value of wheel/rail samples increases rapidly, and the hardness duration is also long. The hardness value of the wheels and rails of the proposed method is in a high horizontal wave, which is 750. Compared with



(a) Rail

(b) Wheels

Figure 10 Tensile strength comparison results.

650, 800 and 700 of the reference [4] method, the reference [5] method and the reference [6] method, the prediction results of the proposed method for wheel/rail hardness values are consistent with the measured values, indicating that the method has higher prediction accuracy and excellent prediction performance.

The reference [4] method, reference [5] method, reference [6] method and this paper are used to predict the tensile strength of wheel/rail, and the results are shown in Figure 10.

From the analysis of the results in Figure 10, it can be seen that with the increase in test time, the tensile strength of wheel/rail shows a fluctuating trend. The predicted range of track tensile strength and wheel tensile strength by the proposed method is 220 MPa∼450 MPa, which is consistent with the measured value. The range of prediction results of reference [4] method, reference [5] method and reference [6] method is 250 MPa∼550 MPa, 330 MPa∼500 MPa and 230 MPa∼420 MPa respectively. It is proved that this method can accurately predict the mechanical properties of heavy load wheel/rail wear.

4 Conclusion

In the contact process of wheel rail rolling friction, the wheel rail bears a large load, which plays an important role in the traction, braking and guidance of the train. This effect directly affects the stability and safety of the train. In order to solve the problems of traditional methods, a new method to predict the mechanical properties of heavy load wheel/rail wear is proposed in this paper. The experimental results show that the predicted results of wear, hardness and tensile strength by this method are 4.1 g, 750 and 220 MPa∼450 MPa respectively, which are basically consistent with the measured results, indicating that the prediction accuracy of this method is high and can be further used in practical applications.

Funding

This paper was funded by School level STP project in 2022: Research on key technologies of non-contact metal magnetic memory pipeline inspection (No. 2022STP010).

References

[1] Peng Q, Ren S, Wang W, et al. The Railway Detection via Adaptive Multi-scale Fusion Processing[J]. Journal of Physics: Conference Series, 2021, 1887(1):012003–012012.

[2] Pires A C, Mendes G R, Santos G, et al. Indirect identification of wheel rail contact forces of an instrumented heavy haul railway vehicle using machine learning[J]. Mechanical Systems and Signal Processing, 2021, 160(1):107806–107817.

[3] Yan S, Deng Y, Hao L, et al. Analysis of Subgrade Vibration and Dynamic Stress of Heavy Haul Railway with High Embankment based on ZL-TNTLM Program[J]. Journal of Physics: Conference Series, 2021, 1965(1):012038–012049.
[4] Cui J T, Guo Y. Research on Wheel/Rail Wear Prediction Model Based on Multivariable Parallel Discrete Computing Method[J]. Mechanical Engineer, 2022(02):130–134.
[5] Wang M, Wang H L, Wang J P. Wear Volume Prediction of Brake Shoes Used in Heavy Freight Wagon Based on DBN[J]. Computer Simulation, 2022, 39(03):134–139.
[6] Tao H Q, Cai X, Zhou Y. Prediction of Metro Wheel Tread Wear Based on Variable Weight Combination Model[J]. Urban Mass Transit, 2020, 23(06):58–62.
[7] Xu W W, Peng J P, Qiu C R. Prediction model of subway pantograph slide pan wear trend based on LSSVR[J]. Railway Computer Application, 2020, 29(01):77–81.
[8] Dong Y G, Yi S, Huang X L, et al. Temperature Distribution of Treads and Wear Prediction during Train Emergency Braking[J]. China Mechanical Engineering, 2021, 32(04):431–438+445.
[9] Andrzej Myslinski, Andrzej Chudzikiewicz. Wear modelling in wheel-rail contact problems based on energy dissipation[J]. Tribology – Materials, Surfaces & Interfaces, 2021, 15(2):138–149.
[10] Sladkova L. A., Neklyudov A. N. A New Look at the Problem of Wear on Wheel Rolling[J]. Journal of Friction and Wear, 2021, 42(2): 101–105.
[11] Mayba I. A., Glazunov D. V. Optimization of Tribotechnical Characteristics of Wheel–Rail Friction Modifiers[J]. Journal of Friction and Wear, 2021, 41(6):517–520.
[12] Zhang H, Ran X, Wang X, et al. Coupling Effects of Yaw Damper and Wheel-Rail Contact on Ride Quality of Railway Vehicle[J]. Shock and Vibration, 2021,15(3):1–18.
[13] Pires A C, Mendes G R, Santos G, et al. Indirect identification of wheel rail contact forces of an instrumented heavy haul railway vehicle using machine learning[J]. Mechanical Systems and Signal Processing, 2021, 160(1):1–10.
[14] Yy A, Yu S, Ds A, et al. A wheel wear prediction model of non-Hertzian wheel-rail contact considering wheelset yaw:Comparison between simulated and field test results[J]. Wear, 2021, 15(1):474–485.

[15] Kvarda D, Galas R, Omasta M, et al. Asperity-based model for prediction of traction in water-contaminated wheel-rail contact[J]. Tribology International, 2021, 157(1):106900–106911.
[16] Maiba I, Glazunov D, Maiba V. Special purpose composite materials for wheel-rail contact[J]. IOP Conference Series: Materials Science and Engineering, 2020, 709(3):033013–033019.
[17] Wang Huan, Yang Guangwu, Ke Xin, et al. Study on the Influence of Geometric Parameters on Load Introduction Factor of Bolted Joints[J]. Computer Simulation, 2020, 37(2):251–257.
[18] Liu P, Yang S, Liu Y. Full-scale test and numerical simulation of wheelset-gear box vibration excited by wheel polygon wear and track irregularity[J]. Mechanical Systems and Signal Processing, 2022, 167(1):108515–108529.
[19] Li S. Correlation analysis method of track irregularity indexes[J]. IOP Conference Series Earth and Environmental Science, 2021, 638(1):012071–012082.

Biographies

Xiao Xue, Associate Professor of School of Electronic and Electrical Engineering in Nanyang Institute of Technology, Nanyang, China. He received his Bachelor of Engineering Science in Electronic Information Engineering from Nanyang Institute of Technology, Henan, China, in 2003; the Doctor Degree of Engineering in detection technology and automatic equipment from China University of Geosciences, Wuhan, China, in 2015. His current research interests include Detection technology, and intelligent control.

Yangbing Zheng, Associate Professor of control science and engineering, with Nanyang Normal University, Nanyang, China. She received her Bachelor of Engineering Science in Electronic Information Engineering from Nanyang Institute of Technology, Henan, China, in 2006; and the Doctor Degree of Engineering in detection technology and automatic equipment from China University of Mining and Technology, Beijing, China, in 2013, respectively. Her current research interests include active robot control, and nonlinear control.

Xin Wang, Senior Engineer of Henan Minghui Construction Group Co.LTD, received his Master of Engineering degree form China University of Geosciences (Wuhan). His current research interests include civil engineering, fluid mechanics and architectural mechanics.