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Research article

The rutting model of semi-rigid asphalt pavement based on RIOHTRACK full-scale track

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Abstract: Semi-rigid asphalt pavement has a wide range of application cases and data bases, and rutting is a typical failure mode of semi-rigid asphalt pavement. The establishment of an accurate rutting depth prediction model is of great significance to pavement design and maintenance. However, due to the lack of perfect theoretical system and systematic research data, the existing rutting prediction model of semi-rigid asphalt pavement is not accurate. In this paper, machine learning and mechanical-empirical model are combined to study the feature selection affecting the rutting evolution and rutting depth model of semi-rigid asphalt pavement. First, the particle swarm optimization random forest model is used to select the important features that affect the evolution of rutting depth. Second, the R-F model based on important features is proposed for the first time, which is compared with modification of rutting model in the Chinese Specifications for Design of Highway Asphalt Pavement (JTG D50-2017) and R-B model based on the improved Burgers model. The results show that the R-F model has more accurate prediction ability and better generalization ability, and it does not need complex data preprocessing and noise reduction. Here, the machine learning method is introduced to analyze the data characteristics, and the R-F rutting depth prediction model framework is innovatively proposed, which greatly improves the applicability and accuracy of the existing model framework.

Keywords: semi-rigid asphalt pavement; rutting depth prediction model; feature selection; R-F model; random forest

1. Introduction

Under the international background of carbon peak and carbon neutralization, the research, design and construction of green, low carbon, long-life pavement is extremely urgent. It has become an urgent requirement for the development of transportation industry to develop long-life pavement technology and ensure the service performance of asphalt pavement in the whole life cycle. However, the current asphalt pavement technology is faced with such basic problems as insufficient data mining, imperfect mathematical theory support, low reliability of relevant design models, and large error in design life estimation. It is urgent to strengthen the research on core issues and break through the bottleneck in this field. Since the completion of Beijing Tianjin Tangshan Expressway in the 1980s, semi-rigid base course materials have gradually become the main road materials in China due to their high bearing capacity, deformation resistance, good frost resistance and the outstanding characteristics of using local materials. So far, semi-rigid base asphalt pavement is still the most important asphalt pavement structure in China. Therefore, the scientific research of semi-rigid pavement is particularly important.

With the increase of semi-rigid asphalt pavement running time, with the rapid growth of traffic volume, the increase of the proportion of heavy vehicles, serious overloading, the typical damage phenomenon of semi-rigid pavement continues to increase. Rutting is a kind of damage form of semi-rigid asphalt pavement, which is a permanent indentation of wheels under the combined action of repeated driving load and climate [1]. It is shown as a longitudinal strip groove along the driving wheel track. In serious cases, prominent deformation will occur on both sides of the rutting, leading to deterioration of the pavement performance. The detection and prediction of pavement rutting can provide important information for decision-makers, and it is of great significance to the structural design, maintenance and repair of asphalt pavement [2, 3].

Over the years, scholars have carried out extensive research on the development of asphalt pavement rutting prediction models and proposed various models to characterize and predict the evolution process of asphalt pavement rutting depth [4]. The research on asphalt rutting has a long history in the world. At the 3rd International Conference on Asphalt Pavement Structure Design in 1972, Barksdale and Romain proposed the layer strain method to predict ruts on flexible pavement [5]. At the 6th International Conference on Asphalt Pavement Structure Design in 1987, Eckmann's research combined dynamic creep test and layer strain method to predict the ruts of full scale test road, and the predicted model showed good agreement with the field measurement results [6]. Eisenmann and Hilmer investigated the effects of wheel load and tire pressure on the amount of rutting in asphalt pavement. They performed full scale tests using different wheel load, tire pressure and wheel sets, then directly measured the amount of rutting, and analyzed the effects of different test conditions on the amount of rutting using decay analysis method. In 2000, Tarvey concluded that the shear characteristics of asphalt roads were nonlinear through experiments on the frequency surface of asphalt roads. In 2006, At the 10th International Conference on Asphalt Pavement Design, Humvey and Monisith conducted an experimental study on rutting of asphalt pavement under different wheel loads, wheel pressures and temperatures; obtained the profile of the experimental section, showing obvious shear deformation at the edge of the wheel track; and established a correct rutting prediction method according to the test to evaluate the shear performance of the mixture [7]. In the condition of high temperature, asphalt mixture shows three kinds of properties, adhesive, elastic and plastic, and it is easier to produce unrecoverable permanent deformation.

Some scholars have studied the relevant models between pavement structure and performance based on mechanical constitutive models, such as the viscoelastic model [8–10], viscoelastic-plastic model [11], viscoelastic-plastic damage model [12], etc. However, how to accurately establish the model and determine the constitutive parameters has been a difficult problem [13]. In the research of empirical model framework, some scholars mainly focus on indicators and mechanical framework, supplement the influence factors such as traffic load [14] and temperature [15], and modify the mechanical model [16, 17]. Relevant scholars have studied the research process of rut prediction model for flexible pavement [18]. However, due to the lack of data and discontinuity, the empirical model framework cannot systematically represent the characteristics of asphalt pavement. At the same time, due to the lack of systematic combination of mechanical research and mathematical model research, the construction of empirical models is limited.

In the world, many countries have carried out full-scale track research to study long-life pavement, and obtained key data for asphalt pavement evolution model research by shortening the loading cycle. The AASHO test track built in the United States in 1959 supported the creation of the world famous MEPDG design method [19]. Since 1984, France has carried out a large number of accelerated pavement loading tests relying on the Nantes Ring Road to continuously verify and improve the French pavement design methods [20]. In the early 1970s, South Africa conducted research on semi-rigid base asphalt pavement structure through large-scale outdoor accelerated loading test, and achieved research results that are still influential in the world [21]. At the end of 2015, the first full-scale track in China, RIOHTRACK, was completed in the Beijing Highway Traffic Test Field [22]. This track basically covers all pavement structure types of high-grade asphalt pavement at home and abroad, which is mainly used to study the rutting deformation evolution law of main asphalt pavement structure and materials and provides key data support for this study.

Different types of pavement structures have different evolution rules of service performance, so we need to determine the performance design model for different types of structures. It is very important to find and build an optimized model frame with high applicability for all pavement structures. On the basis of the optimized evolution model, it is the main technical route to determine the critical state through the experimental data of the track.

On the basis of machine learning and mechanical-empirical model research, this paper carried out research and verification on the full-scale track data in Beijing, and innovatively proposed the R-F rutting prediction model framework suitable for semi-rigid asphalt pavement. The particle swarm optimization random forest model is used to select the most important features that affect the evolution of rutting depth. The R-F model based on important features is proposed for the first time, and is compared with the modification of rutting model in the Chinese Specifications for Design of Highway Asphalt Pavement (JTG D50-2017) and R-B model based on the improved Burgers model.

The rest of this paper is organized as follows. Section 2 presents the rutting depth model based on the RIOHTrack track, including data set sources, feature selection of the random forest algorithm based on particle swarm optimization and the rutting depth model framework. The main results and discussion of model fitting are given in Section 3. Section 4 gives the brief conclusion of this paper.

2. Model construction

2.1. Full-scale track test

Pavement performance is a multi-factor long-term evolution process [23]. It is an extremely time-consuming project to analyze the performance using the real road operation data. Therefore, the accelerated loading test is an effective test method to simulate the real road operation. It can accelerate the road performance by increasing the test load of vehicles, and simulate the long-term performance of the road structure at a lower cost and in a shorter time. The RIOHTRACK accelerated loading test track was completed in China in November 2015, and it is the first full-size test platform for long-life asphalt pavement in the world, aiming to verify the serviceability design model of long-life asphalt pavement. The total length of the track is 2039 meters, which is a closed curve consisting of multiple straight lines and circular curves. It is arranged symmetrically in a north-south direction. A total of 25 different asphalt pavement structures (including 19 main test pavement structures and 6 anti rutting pavement structures) and 13 typical cement concrete pavement structures have been built on the RIOHTRACK track. RIOHTRACK is very representative of various pavement structures, covering no less than 90% of pavement types commonly used in asphalt highways in China. Among them, 19 main test pavement structures are divided into six different types: thin asphalt concrete semi-rigid base structure STR1-STR3, common semi-rigid base structure STR6-STR9, rigid composite base structure STR4 and STR5, inverted structure STR10 and STR12, thick asphalt concrete base structure STR11 and STR13-STR17 and full depth asphalt concrete structure STR18 and STR19. The detailed structural thickness and material information of 19 main test pavement structures are shown in Figure 1 [24].

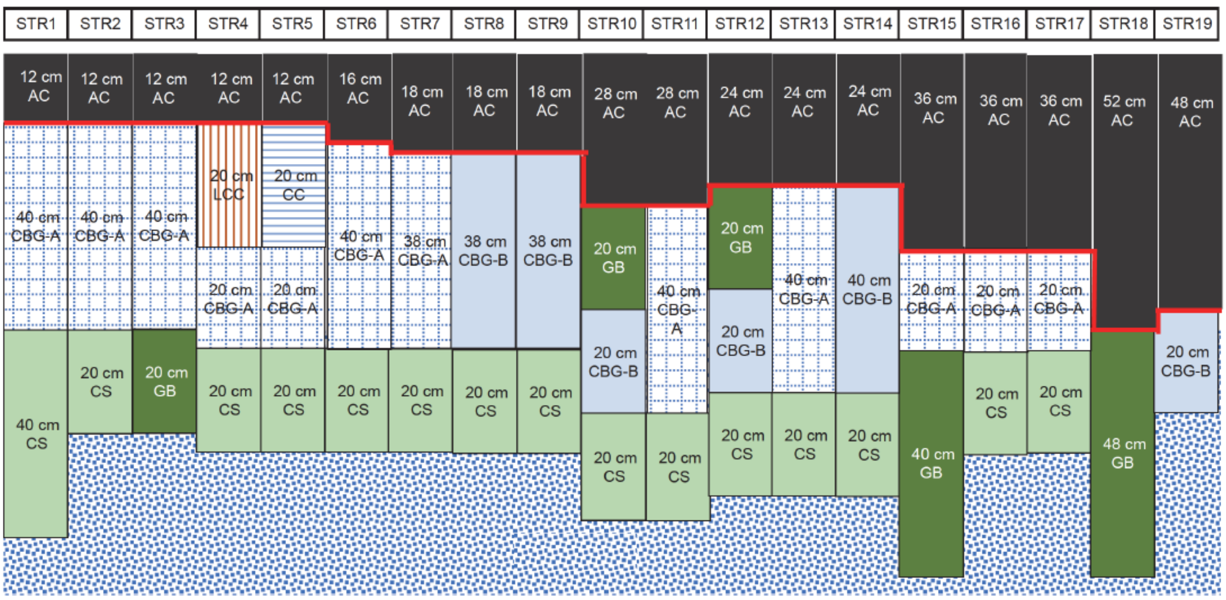

Figure 1. The total thickness of the pavement structure varies from 68 to 100 cm. A total of 21 kinds of asphalt mixture surface and base material, 5 kinds of cement stabilization material and 1 kind of graded gravel base material are combined to form 19 kinds of pavement structure with wide stiffness domain base material.

RIOHTRACK full-scale track loading test was started in November 2016. Four 10 wheel Steyr heavy trucks were used to drive at the speed of 40–60 km/h, and the axle load of loaded vehicles was $16t$ per axle. Track performance detection includes two ways: One is real-time monitoring, and the other is periodic detection. Real-time monitoring includes 24 h acquisition of stress-strain information within the structure with a frequency value of 2000 Hz, induction vehicle axle load monitoring and structure internal and external environment monitoring. Periodic testing includes but is not limited to structural bearing capacity, surface function, damage and serviceability testing. Based on massive data collection and analysis, the evolution law of pavement performance is characterized, as well as the significant differences of performance between typical asphalt pavement structures.

RIOHTRACK full-scale track is located in Beijing, with an average temperature of -4.6 $^{\circ}C$ in the coldest month and 25.8 $^{\circ}C$ in the hottest month. The temperature data of pavement structure in RIOHTRACK track is selected as the basic data for analysis. The structure and layout depth of the temperature sensor are shown in Figure 2.

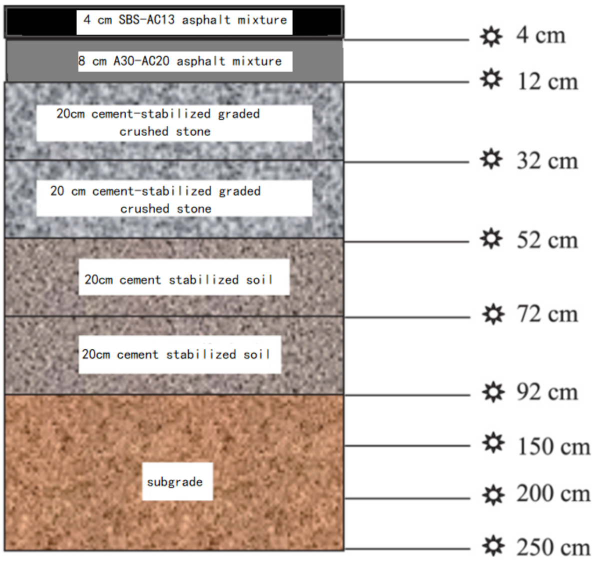

Figure 2. The internal temperature of RIOHTRACK pavement structure is detected by temperature sensors of different depths. The shallowest measuring point is 4 cm away from the road table, and the deepest measuring point is 250 cm away from the road table. The temperature acquisition frequency is 10 min. The accuracy of the sensor is 0.15 $^{\circ}C$, using a PT100 platinum resistance temperature sensor with a measurement range of -50 –100$^{\circ}C$.

2.2. Analysis of relevant characteristics of asphalt pavement

According to the mechanical properties of asphalt mixture and the research experience of existing models, there are many factors related to permanent deformation of asphalt pavement, including temperature, humidity, load, axial load, radiation, pressure and so on. However, how to select the key features related to rutting depth is particularly important for further model construction and performance prediction.

In order to improve the generalization ability of the model and reduce the computational complexity, this paper extends the rutting feature selection method by selecting subsets of existing features without feature transformation.

In essence, feature selection has two requirements: One is the objective function, and the other is the search strategy. Objective functions generally fall into two categories: filters and wrappers. The corresponding methods are called filter-based feature selection and wrapper-based feature selection. In this paper, we choose the random forest classification model based on Gini coefficient as the packaging of the objective function, and we use the search strategy of particle swarm optimization to select features. Among them, the relevant objective functions and search strategies are as follows.

2.2.1. Objective function

In the wrapper of this model, the objective function is set as classifier mode, and the classifier is set as random forest classification model. The objective function of this project is set as Figure 3:

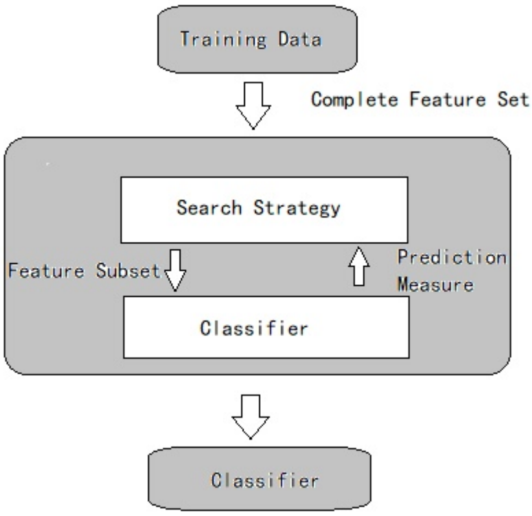

Figure 3. Objective function.

The random forest has put back sampling to solve the lack of universality of the wrapper, and the particle swarm optimization search strategy to solve the problem of slow execution speed.

Random forest. The random forest adopts the resampling technique, which selects k samples from the original N training samples set again repeatedly, generates a new training sample subset, then generates N classification trees according to the sample subset and finally forms a random forest [25]. Its essence is the improvement and promotion of the decision tree algorithm. It bundles several decision trees together, each dependent on a relatively independent subset of the sample. Random forest integrates multiple decision trees through the idea of ensemble learning. Among all the current classification and regression algorithms, random forest has higher accuracy. It also runs efficiently on large data sets and can handle input samples with high dimensional characteristics without reducing the data's low dimensions [26]. It can evaluate the importance of each feature in the classification problem and obtain the unbiased estimation of the internal generation error in the generation process. For the default value, good results can also be obtained.

The super parameters in the random forest model mainly include the number n of decision trees and the number m of attribute feature subsets, which run through the construction process of the random forest model. Subjective selection or traditional ergodic parameter selection methods inevitably affect the efficiency and accuracy of the model. In this paper, the particle swarm optimization strategy is introduced to solve the parameter optimization problem of the model by simulating the movement process of the biological population.

The Gini coefficient. This paper calculates the impurity of nodes by Gini coefficient to measure the importance of features [27]. The Gini coefficient is the probability that a randomly selected sample in the sample set will be misclassified. The smaller the Gini index is, the smaller the probability that the selected samples in the set will be mistaken, that is to say, the higher the purity of the set; conversely, the more impure the set is. When all the samples in the set are of one class, the Gini index is 0, that is, all the values in the child nodes belong to the same type of classification. At this time, the value of the Gini coefficient is the minimum, and the purity of the child nodes is the highest. If there are k classes in the decision tree, and the probability that the sample belongs to the kth class is p_k, then the Gini coefficient of the probability distribution of the class is

$$Gini(p) = \sum_{k=1}^{K} p_k(1 - p_k) = 1 - \sum_{k=1}^{K} p_k^2. \tag{2.1}$$

When we traverse each segmentation point of each feature of data set D, feature $A = a$ is used to divide D into two parts. One part is called D_1, that is, the sample set satisfying $A = a$, and the other part is called D_2, that is, the sample set not satisfying $A = a$. Then, under the condition of feature segmentation $A = a$, the Gini coefficient of D is

$$Gini(D, A) = \frac{|D_1|}{|D|}Gini(D_1) + \frac{|D_2|}{|D|}Gini(D_2). \tag{2.2}$$

where $Gini(D)$ represents the uncertainty of set D, and $Gini(D, A)$ represents the uncertainty of set D after $A = a$ segmentation.

The random forest iterates all possible segmentation points of the feature subset of the decision tree to find the feature segmentation point with the smallest Gini coefficient, and it divides the data set into two subsets until the stopping condition is met.

2.2.2. Search strategy

Assuming that the best subset of N features is selected, the number of feasible combinations is 2^N. The algorithm that exhausts all the original features needs a powerful search strategy to guide the feature selection process, because it needs to explore all possible combination spaces [28].

Particle swarm optimization algorithm. Particle swarm optimization algorithm is a swarm intelligence algorithm that simulates the foraging behavior of birds to solve optimization problems [29]. The algorithm searches the feasible solution value of the region around the particle, and it then calculates the fitness by replacing the fitness function. The speed and direction of the particle iteration process are adjusted by comparing the fitness. In the adjustment process, the global influence degree and the particle's own influence degree are controlled by controlling the size of the learning factor.

In the actual training process, the decision tree scale and attribute feature subset in the random forest model were taken as the attributes of particles in the particle swarm optimization algorithm, and the Gini coefficient was used as the fitness function to train the model repeatedly and calculate the classification accuracy of the model to evaluate the classification effect of the model.

The specific training process of the selection algorithm based on relevant features is as the following steps:

Step 1: Put back sampling on the data set, and take the selected samples as the training set D and the unselected samples as the validation set Y;

Step 2: Initialize parameters, including particle attributes (number of decision trees T, feature attributes N), number of iterations n_{maxgen}, learning factor c_1, c_2, inertia coefficient w, etc;

Step 3: Combined with the random forest classifier, the average classification accuracy of the model was calculated by cross-validation, and the Gini coefficient of the random forest was calculated;

Step 4: Compare the fitness value of the particles obtained under the current number of iterations, and update the particle attributes, motion direction and velocity. kg represents the current evolutionary algebra, the position of the particle in the solution space is expressed as X_i, and the velocity is expressed as V_i;

$$V_i^{kg+1} = w(t)V_i^{kg} + c_1 r_1(P_i^{kg} - X_i^{kg}) + c_2 r_2(BestS^{kg} - X_i^{kg}), \tag{2.3}$$

$$X_i^{kg+1} = X_i^{kg} + V_i^{kg}. \tag{2.4}$$

Step 5: Save the particle attribute with the highest fitness value of the current iteration as the optimal particle, stop the iteration when the maximum number of iterations is reached, and output the particle attribute T, N and classifier index.

2.3. The construction of rutting prediction model framework of semi-rigid asphalt pavement

The rutting prediction of asphalt pavement is a difficult and key problem in asphalt pavement research. The mechanical properties, functional properties, long-term performance attenuation laws and damage characteristics of different pavement structure combinations are quite different, which should be considered in the pavement structure combination. The comprehensive design of subgrade and pavement also requires that the subgrade has sufficient bearing capacity and suitable dry and wet conditions, so that the combination of pavement structures can adapt to the subgrade bearing capacity, humidity conditions and soil types. Therefore, our rutting prediction model needs to fully consider the relevant mechanics, experience, functions and specification requirements. This section introduces three rutting models for semi-rigid asphalt pavement structure: R-F model, R-B model based on modified Burgers model and the modification of the rutting model in JTG D50-2017, where R-F is short for Rutting from Feature Selection, and R-B model is short for Rutting from Burgers.

2.3.1. R-F model framework

Rutting depth is the nonlinear deformation of asphalt pavement, which is the result of the coupling between the features. Based on the analysis of the main features of machine learning, the random forest features based on particle swarm optimization are selected under different structures, and the accumulated axial load is emphasized to fit the rut.

According to the pavement performance observation data obtained from the RIOHTRACK full-scale track accelerated loading test, the importance values of 10 characteristic indicators that affect the rutting depth change are obtained by using the feature selection method introduced in subsection 2.2, as shown in Figure 4. Among 10 characteristic indicators that affect the rutting depth change, the influencing factors whose characteristic importance index exceeds 0.15 mainly include the number of axle load and the pavement structure. Therefore, for a semi-rigid asphalt pavement with a specific pavement structure, we mainly consider the impact of cumulative axle load times on the rutting depth of semi-rigid asphalt pavement.

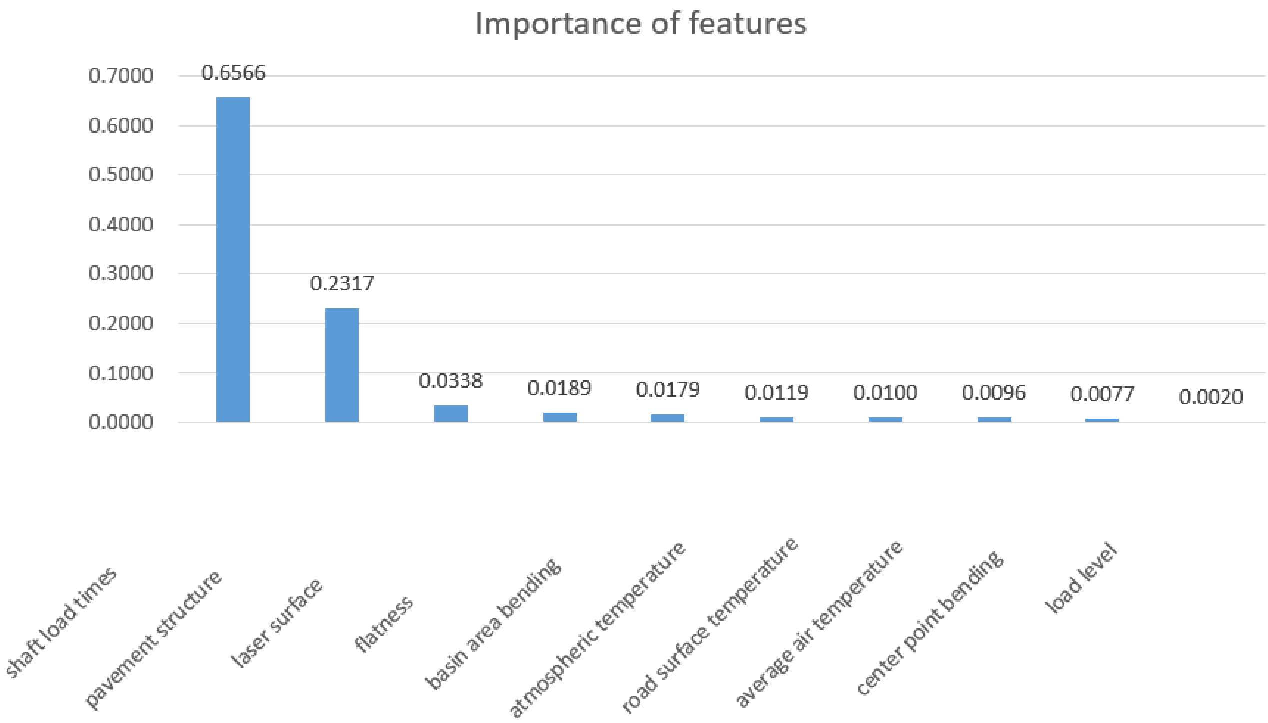

Figure 4. The importance value of 10 features associated with rutting of asphalt pavement is obtained by the improved random forest algorithm and based on the semi-rigid pavement data of RIOHTRACK full-scale track. The sum of the above feature values is 1.00.

According to the performance data analysis of asphalt pavement, different function forms of various characteristic variables are studied and analyzed. Based on the data of exponential empirical model framework and RIOHTRACK full-scale track, through a large amount of data analysis and simulation, the R-F model framework is proposed.

The R-F model framework describes the rutting depth of semi-rigid asphalt pavement through the nonlinear transformation of the cumulative number of axle load actions, whose type is a power function, and the specific expression is shown in Eq (2.5):

$$RD = \sum_{k=1}^{b} (a_k N_s^k). \tag{2.5}$$

where RD is the rutting depth (unit: 0.1 mm); Ns is the cumulative number of axial loads taken as logarithm; b, a_k are the regression coefficients of the prediction model.

After a lot of calculation and analysis, the model framework has the advantages of few parameters, convenient calculation and high fitting accuracy. It is applicable to predicting rutting and related environmental conditions of semi-rigid asphalt pavement on RIOHTRACK full-scale track, and it has strong applicability and generalization ability, which is proved in the following sections.

For further comparative analysis and validation, two other model frameworks are described below. Their prototype has already achieved good results in different areas and has been improved and optimized here.

This section innovatively proposes the R-F model framework for rutting depth prediction of semi-rigid asphalt pavement. In the next section, we will show that compared with the improved mechanical-empirical R-B model framework and the modification of the rutting model in JTG D50-2017, the proposed R-F model framework has shown surprising results in the rutting research of semi-rigid asphalt pavement. It is verified by using RIOHTRACK full-scale track accelerated loading test data.

2.3.2. R-B model framework

Asphalt structural materials, including asphalt, sand and other materials, have highly nonlinear characteristics, with temperature and humidity correlation, so there are specific requirements for the construction of pavement models, including mechanical constitutive model, mathematical model, artificial intelligence model. As the main comparison model, the improved Burgers constitutive model was selected. This paper selects the improved Burgers model structure, mainly from the Burgers constitutive model, to supplement the plastic components, better reflecting the evolution of asphalt pavement in different stages of the physical characteristics of elasticity, viscoelasticity, viscoelastic-plastic [30,31].

The Burgers model is a widely applicable mechanical constitutive model, which is a four-element model derived from the series of Maxwell model and Kelvin model and belongs to the linear viscoelastic model. The Maxwell model is composed of an elastic element with elastic modulus E_1 and a dashpot element with viscosity coefficient η_1 in series. The Kelvin model is composed of an elastic element with elastic modulus E_2 and a dashpot element with viscosity coefficient η_2 in parallel [32].

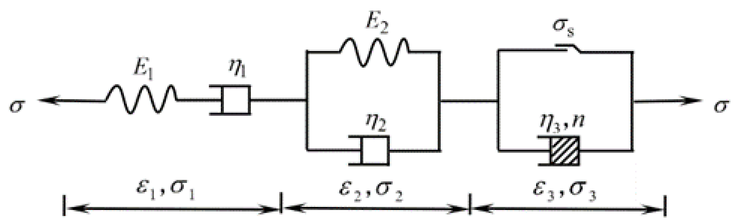

Figure 5. Six-element nonlinear viscoelastic-plastic model.

The improved Burgers model, which is called R-B model in this paper, is a nonlinear viscoelastic plastic model formed by the nonlinear viscoplastic unit and Burgers model in series, and it can well describe the accelerated creep stage of asphalt mixture. When $\eta_0 \leq \eta_s$, the model degenerates into the Burgers model, and the creep deceleration and constant velocity stages of asphalt mixture can be described. When $\eta_0 > \eta_s$, the mode is a nonlinear viscoelastic-plastic model, which can describe the creep acceleration stage of asphalt mixture. According to the data, the yield stress limit σ_s of asphalt is 0.05 MPa.

The nonlinear viscoelastic-plastic model is shown in Figure 5. The creep equation of the nonlinear viscoelastic-plastic model is obtained as follows:

$$RD = \frac{\sigma}{E_1} + \frac{\sigma}{\eta_1} + \frac{\sigma}{E_2}(1 - e^{(-E_2/\eta_2 t)}) + \Gamma(\sigma - \sigma_s)/\eta_3 t^n. \tag{2.6}$$

Among them,

$$\Gamma(\sigma - \sigma_s) = \begin{cases} 0, & \sigma \leq \sigma_s \\ \sigma - \sigma_s, & \sigma > \sigma_s \end{cases} \tag{2.7}$$

where RD is rutting depth, 0.1 mm, σ is the constant stress, σ_s is the yield stress, E_1 and E_2 are the moduli of elasticity, η_1, η_2 and η_3 are the coefficients of viscosity, and n is the creep index (reflecting the accelerated creep rate of the asphalt mixture).

Based on the Burgers model, plastic components are added to the model to meet the fitting requirements of the rut evolution process of asphalt pavement, making the model more appropriate to the actual evolution situation. Meanwhile, taking into account the temperature sensitivity of asphalt materials, correction coefficients e^{aT} and e^{bT} are introduced for elastic deformation and viscous deformation, respectively. That is,

$$RD = \frac{\sigma}{e^{aT}E_1} + \frac{\sigma}{e^{bT}\eta_1} + \frac{\sigma}{e^{aT}E_2}(1 - e^{-\frac{e^{aT}E_2}{e^{bT}\eta_2}t}) + \frac{\Gamma(\sigma - \sigma_s)}{e^{bT}\eta_3}t^n. \tag{2.8}$$

Asphalt mixture is a typical temperature-sensitive viscoelastic-plastic material [33]. The constitutive equation of the model above describes how the deformation of asphalt mixture mainly changes with time. There is no representative variable of temperature, which cannot directly reflect the effect of temperature on deformation. Therefore, the correction coefficient of the environmental temperature on the elastic deformation characteristics of asphalt mixture is set as e^{aT}, and the correction coefficient of the viscous deformation characteristics of asphalt mixture is set as e^{bT}. The time variable is replaced by the number of axial loads with high sensitivity, $N_s/10000$. Based on the above analysis, the frame structure of mechanical-empirical model for predicting rutting depth of semi-rigid asphalt pavement is as follows:

$$RD = 100[\frac{1}{e^{aT}E_1} + \frac{N_s/10000}{e^{bT}\eta_1} + \frac{1}{e^{aT}E_2}(1 - e^{-\frac{e^{aT}E_2}{e^{bT}\eta_2}}(N_s/10000)) + \frac{\Gamma(\sigma - \sigma_s)}{100e^{bT}\eta_3}(N_s/10000)^n]. \tag{2.9}$$

where

RD – rutting depth;

T – ambient temperature;

N_s – cumulative times of standard axle load;

E_1 – elastic modulus of Kelvin model in the predicted model;

E_2 – elastic modulus of Maxwell model in the prediction model;

η_1 – viscosity coefficient of Kelvin model in the predicted model;

η_2 – viscosity coefficient of Maxwell model in the prediction model;
η_3 – viscosity coefficient of the viscoplastic component in the prediction model;
a, b – regression coefficients of the predictive model.

2.3.3. Modification of rutting model in JTG D50-2017

The current asphalt pavement design specification in China is the Specifications for Design of Highway Asphalt Pavement (JTG D50-2017), which was approved by the Ministry of Transport of the People's Republic of China and issued in September 2017 as the industrial standard of highway engineering. According to the analysis of RIOHTRACK full-scale track data, this specification is closer to the actual situation of asphalt pavement in China than the international standard, so the rutting depth model in the 2017 version of the specification is used as the basic framework of rutting depth model in our study.

According to the requirements of JTG D50-2017, asphalt pavement materials should be designed and material design parameters determined on the basis of technical and economic demonstration according to highway grade, traffic load grade, climatic conditions, functional requirements of each structural layer and local material characteristics. The requirements of raw material properties and mixture composition properties of each structural layer shall be in accordance with the relevant provisions of current specifications JTG F40 and JTG/T F20, and the shall be determined in combination with engineering characteristics and local experience. The determination of springback modulus of subgrade top surface should conform to relevant provisions of current specification JTG D30.

According to the rut depth prediction model introduced in JTG D50-2017, the permanent deformation of asphalt mixture in different layers was obtained through rut test under standard conditions. The permanent deformation of each layer and the total permanent deformation of asphalt mixture layer are calculated according to the following formula:

$$R_a = \sum R_{ai}, \tag{2.10}$$

$$R_{ai} = 2.31 \times 10^{-8} k_{R_i} {T_{pef}}^{2.93} {P_i}^{1.8} {N_{e3}}^{0.48} (h_i/h_0) R_{oi}. \tag{2.11}$$

where
R_a – permanent deformation of asphalt mixture layer (mm);
R_{ai} – permanent deformation of the i th layer (mm);
n – number of layers;
T_{pef} – equivalent temperature of permanent deformation of asphalt mixture layer;
N_{e3} – the cumulative action times of equivalent design axle load on the design lane during the design service life or the period from the opening to the first rut maintenance;
h_i – the ith layer thickness (mm);
h_0 – thickness of rutting test specimen (mm);
R_{oi} – When the test temperature of ith layered asphalt mixture is 60 degrees, the pressure is 0.7 MPa, and the loading times is 2520 times, the permanent deformation of rutting test (mm);
k_{R_i} – comprehensive correction coefficient;
P_i – vertical compressive stress on the top surface of the ith layer of asphalt mixture was calculated according to the elastic layered system theory.

For the semi-rigid asphalt pavement structure of RIOHTRACK full-scale track, the value of h_i/h_0 is adjusted to 1, the comprehensive correction coefficient $k_{R_i}$is adjusted to 1, and the regression coefficients a, b, c and d are introduced. The modified rutting depth frame model is shown in Eq (2.12):

$$R = a!`{T_{pef}}^{b} {P_i}^{c} {N_{e3}}^{d} R_{oi}. \tag{2.12}$$

Based on Burgers improved R-B model and JTG D50-2017 design specification framework, this section innovatively proposes an applicability model based on rut prediction of semi-rigid asphalt pavement, and further verifies it through loop data. Both models have achieved good results under the actual measurement data.

3. Results and discussion

This paper mainly studies the rutting evolution law of semi-rigid asphalt pavement, so the semi-rigid asphalt pavement structures STR1-STR3 and STR6-STR9 in the RIOHTRACK track are selected for research, and the data cycle is 2017–2020. The data of semi-rigid pavement structures STR1-STR3 and STR6-STR9 used are actually collected without complex data processing. Take STR9 data as an example, as shown in Figure 6. It can be seen from the figure that there is no obvious linear relationship between rutting depth and each boundary data. In different structural forms, bending area shows obvious time dependence. With the increase of time and cumulative loading times, the rutting depth rises in the overall impact.

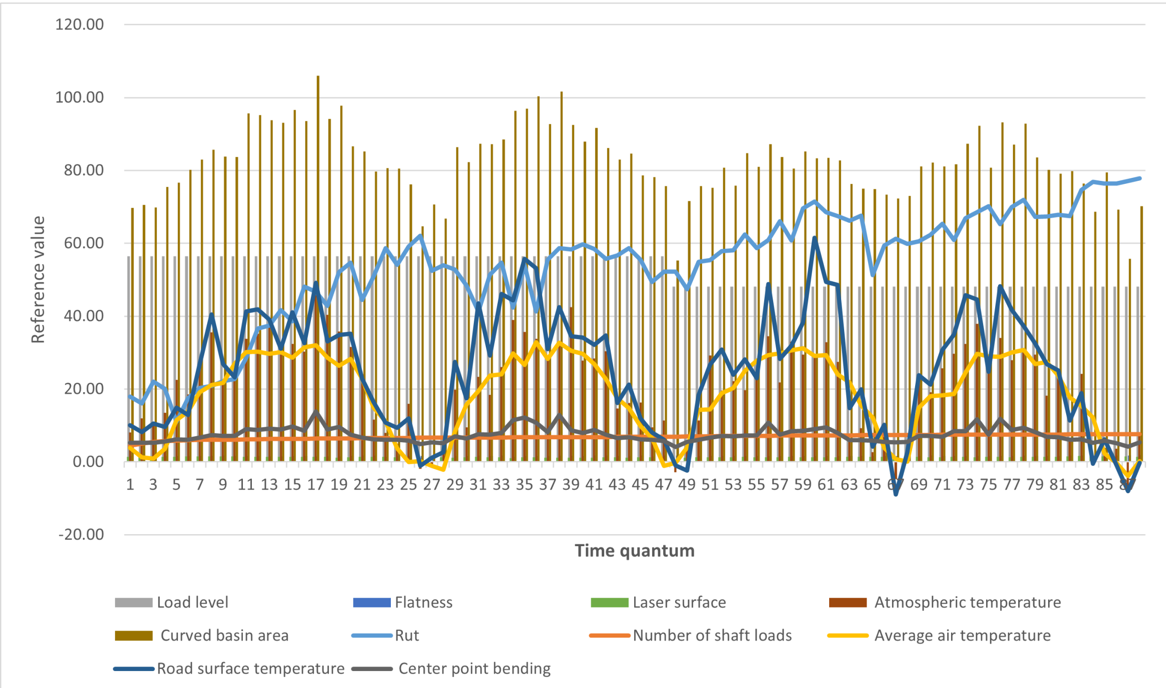

Figure 6. Related data of semi-rigid asphalt pavement STR9. It can be seen that the rutting depth shows a trend of oscillation rising, and there is a nonlinear relationship between the rutting depth and each boundary data.

Based on the above observation data and through feature selection, this section obtains the model manifestations of different orbits under the three model frameworks, a total of 21, which are not expanded here. Among the three model frameworks, the R-F model is the most standardized and has the best effect, R-B model is the most complex, R-2017 model is the simplest, and its accuracy is also affected.

Through the established R-F, R-B and R-2017 regression models, the measured full-scale track data were used to obtain the following regression results through data simulation and calculation:

Table 1. The correlation coefficient of each pavement structure obtained based on different rutting depth prediction models and the average correlation coefficient R-avg of all semi-rigid pavement structures, where the closer the value is to 1, the better the regression effect.

Model/Track	STR1	STR2	STR3	STR6	STR7	STR8	STR9	R-avg
R-F	0.964	0.964	0.960	0.939	0.959	0.963	0.948	0.957
R-B	0.945	0.860	0.910	0.908	0.947	0.953	0.933	0.922
R-2017	0.927	0.944	0.901	0.878	0.938	0.949	0.905	0.920

It can be seen from Table 1 that the regression coefficient of R-F model is balanced. For each semi-rigid pavement structure, without complex data processing and noise reduction, the correlation coefficient based on R-F model is higher than that based on R-B model and R-2017 model. In addition, the average correlation coefficient R-avg of R-F model framework for all semi-rigid pavement structures in the RIOHTRACK track is 0.957, which is higher than that of the other two model frameworks. Therefore, the R-F model has strong generalization ability, and has high accuracy and versatility for predicting rutting depth of semi-rigid asphalt pavement.

Taking STR9 data as an example, combined with the above model frameworks in Section 2, through nonlinear regression calculation and calculation, the model forms of different contents under the three model frameworks are obtained. The details are as follows:

$$RD_{R-F} = -39979.174 + 25744.635Ns - 4797.309Ns^2 + 14.954Ns^3 + 2.174Ns^4 + 32.283Ns^5 - 7.215Ns^6 + 0.598Ns^7 - 0.0176Ns^8. \tag{3.1}$$

$$RD_{R-B} = 100[\frac{1}{e^{-0.00329T}!`E_1} + \frac{Ns/10000}{e^{-0.00256T}!`\eta_1} + \frac{1}{e^{-0.00329T}!`E_2}(1 - e^{-\frac{e^{-0.00329T}!`E_2}{e^{-0.00256T}!`\eta_2}}(Ns/10000)) + \frac{\Gamma(\sigma - \sigma_s)}{100e^{-0.00256T}\eta_3}(Ns/10000)^n]. \tag{3.2}$$

$$RD_{R-2017} = 0.0616{T_{pef}}^0{P_i}^0{N_{e3}}^{3.5915}. \tag{3.3}$$

The following are the parametric statistics of the three models R-F, R-B and R-2017 for the nonlinear regression of STR9 data. It can be seen that all the statistical indicators of R-F are better than R-B model, and those of the R-B model are better than R-2017 model to a certain extent.

Table 2. Statistical results of STR9 data under three model frameworks: $RMSE$-Root Mean Square Error, SSE-The sum of squares error, R-multiple correlation coefficient, DC-Determination factor, $Chi - square$ and $F - Statistic$ Coefficient. From the perspective of each index, R-F model framework is better than R-B model framework and R-2017 model framework.

Model/Statistics	$RMSE$	SSE	R	DC	$Chi - Square$	$F - Statistic$
R-F	5.177	2358.756	0.948	0.894	29.757	682.104
R-B	6.050	3221.630	0.933	0.855	39.910	507.949
R-2017	12.754	14314.032	0.905	0.357	134.291	374.013

It can be seen from the above results that the correlation coefficients of the three model frameworks on STR9 data are all greater than 0.92, among which the R-F model has the best effect. R-F model framework can be applied to 7 structural data of semi-rigid asphalt pavement, which has good universality and is a good result of exploration. The measured data can still achieve good results if applied directly to the above model framework without processing. The research results of the article have the value of further deepening.

According to the model expression form based on the test data of RIOHTRACK full-scale track, the rutting change of semi-rigid asphalt pavement STR9 has a significant nonlinear correlation with the number of axle load, but it has little relationship with temperature. Through the below presentation, it can be clearly seen that among the three model frameworks, R-F model has the best fitting effect and good smoothness, which is conducive to further research in various different scenarios. The fitting curve and residual figure are shown in Figures 7–9.

The data of the full-scale track show the strong correlation between rutting and load data, and the weak correlation between rutting and other factors. There are several reasons for this conclusion. First, the cycle and form of loop loading lead to the inherent evolution law, which needs further detailed research. Second, due to the environmental factors where the loop is located, some boundary thresholds have not been triggered, and there is no correlation in data. Third, due to the influence of construction quality and sensor accuracy, there is some distortion in the collected data, which requires further correction and processing of the data.

Model research is affected by such possible factors as inaccurate transmission of measured data and weak model robustness caused by a single data source. In order to further improve research results, it is necessary to further improve data analysis and preprocessing, and add data of different dimensions, geology, axial load and other conditions for verification and research.

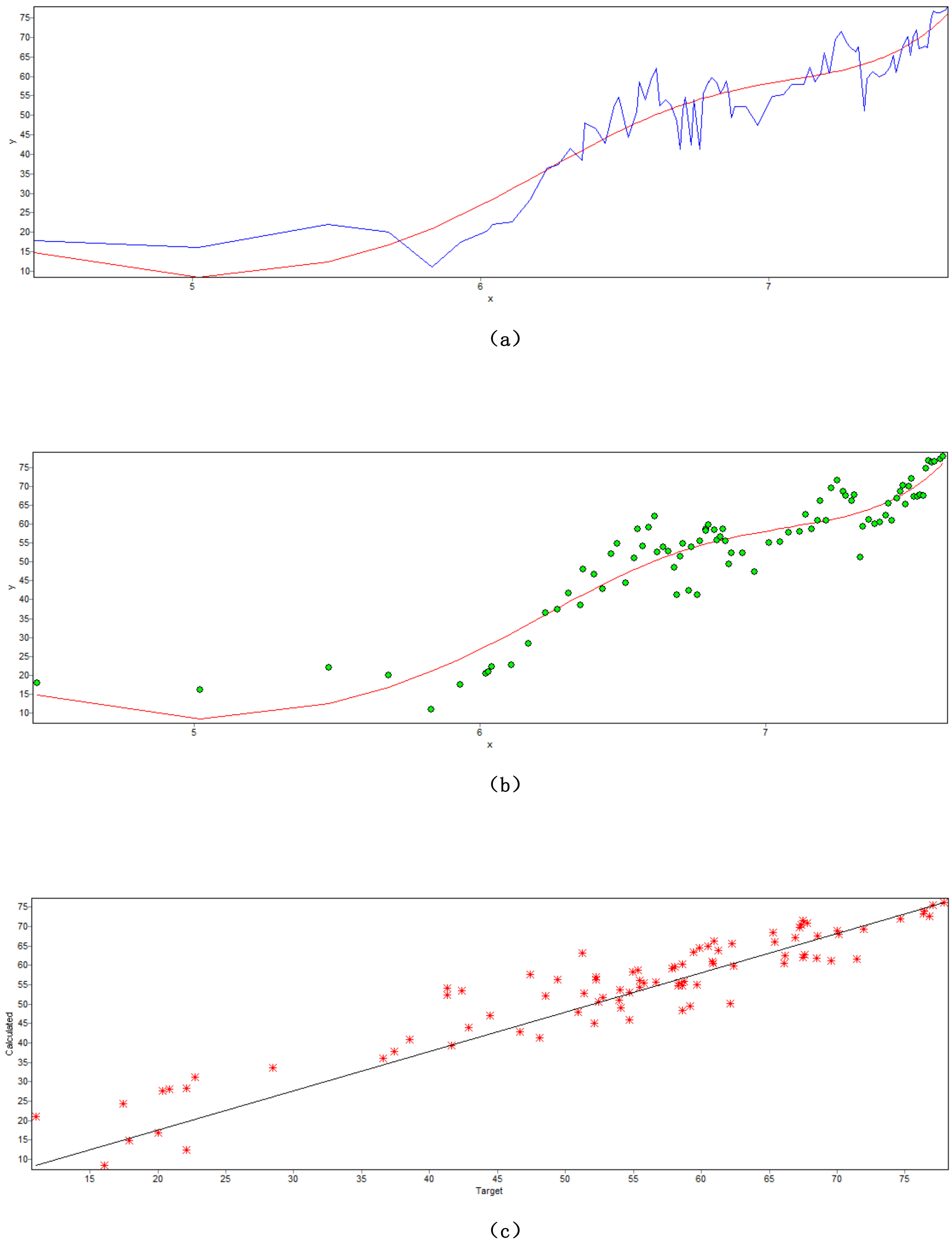

Figure 7. Performance of R-F model frame obtained by fitting the data of semi-rigid asphalt pavement structure STR9: (a) The blue curve represents the actual data, and the red curve represents the fitted nonlinear curve. (b) The green represents the actual data, and the red curve is the fitted nonlinear curve. (c) Residual diagram of the fitting curve, and the uniform distribution indicates that the fitting effect is better.

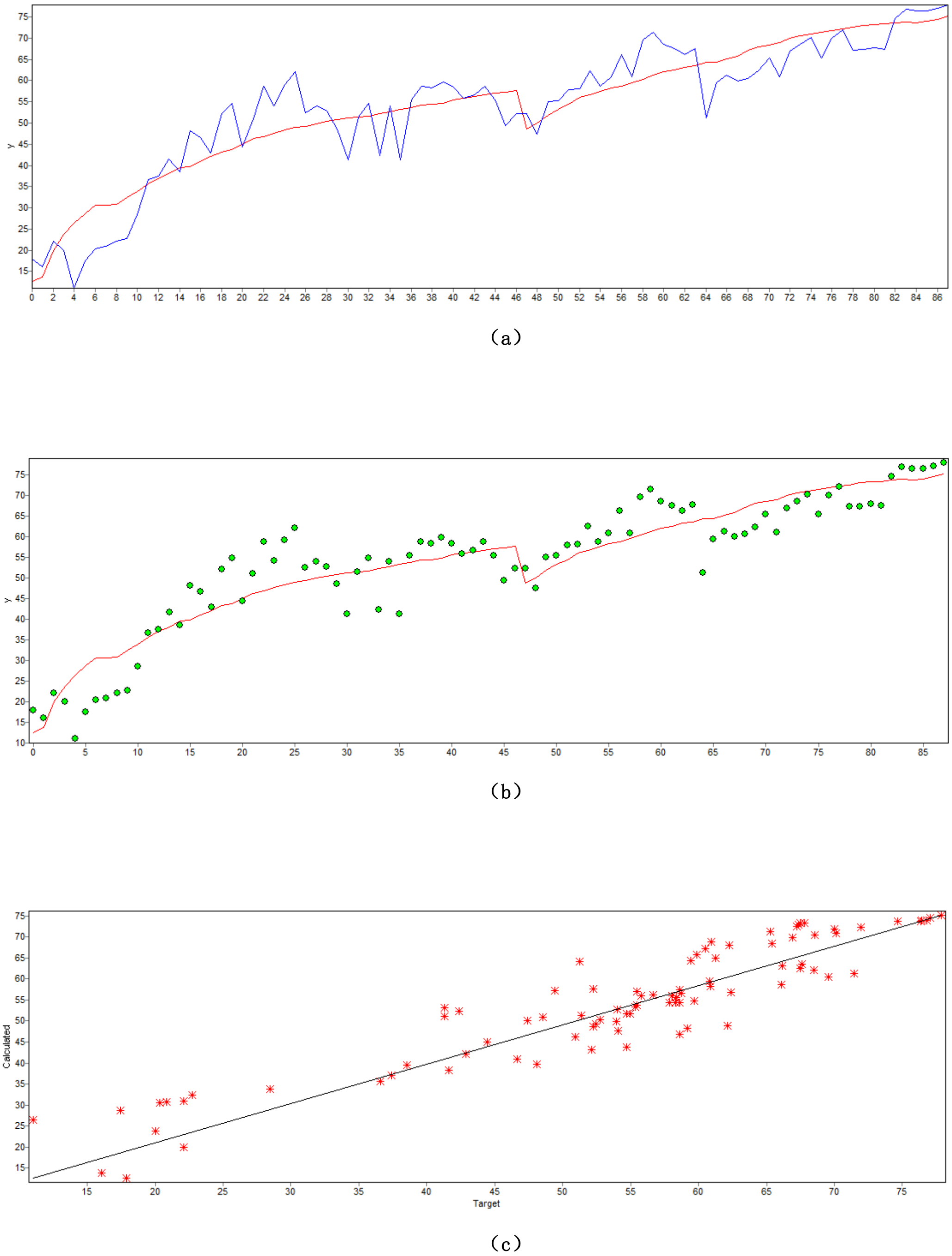

Figure 8. Performance of R-B model frame obtained by fitting the data of semi-rigid asphalt pavement structure STR9: (a) The blue curve represents the actual data, and the red curve represents the fitted nonlinear curve. (b) The green data represents the actual data, and the red curve is the fitted nonlinear curve. (c) Residual diagram of the fitted curve.

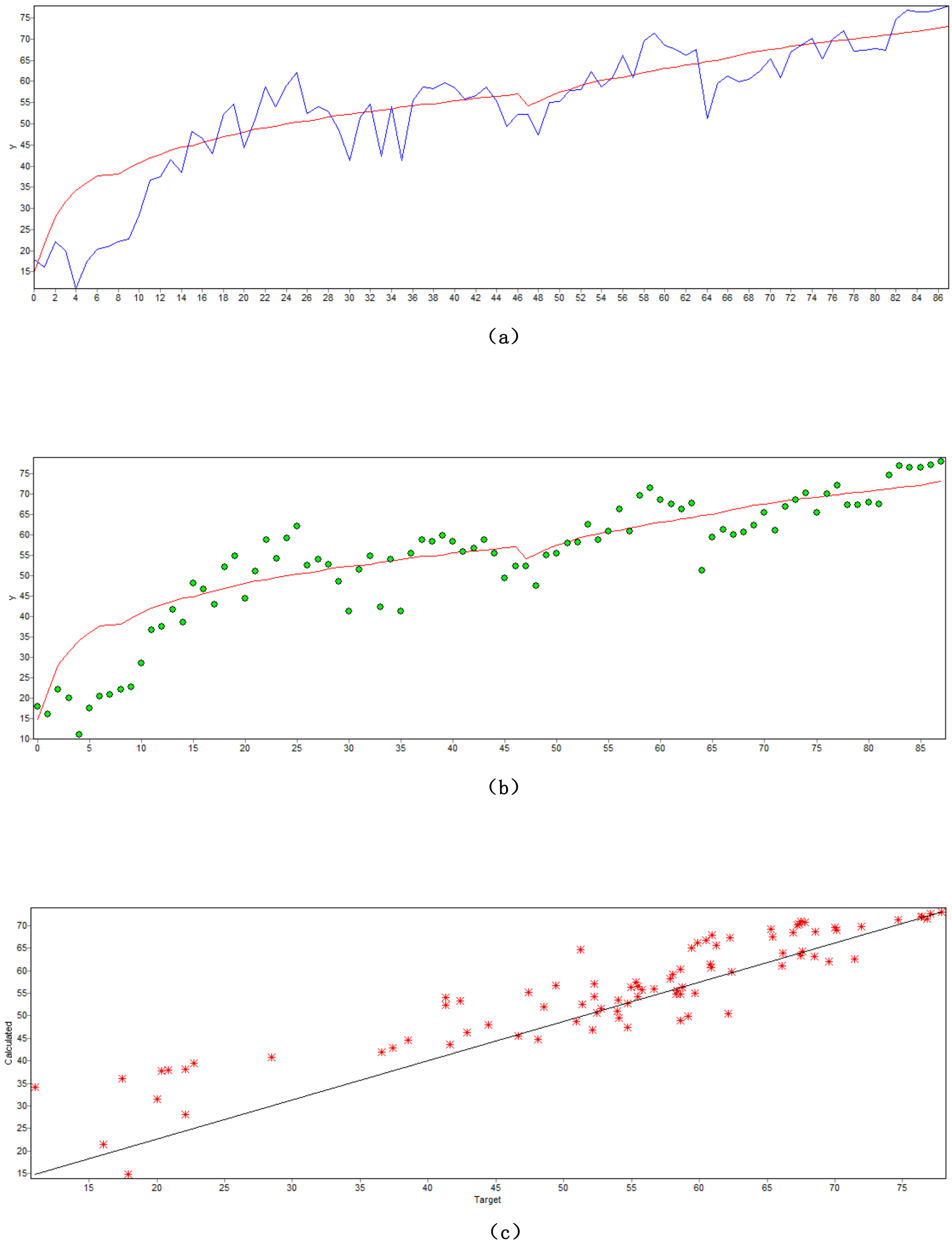

Figure 9. Performance of R-2017 model obtained by fitting the data of semi-rigid asphalt pavement structure STR9: (a) The blue curve represents the actual data, and the red curve represents the fitted nonlinear curve. (b) The green data represents the actual data, and the red curve is the fitted nonlinear curve. (c) Residual diagram of the fitted curve.

4. Conclusions

The main research objective of this paper is to build an explicit rutting prediction model for semi-rigid asphalt pavement. This paper innovatively proposes the R-F rutting model framework. Through model research and data analysis, the R-F rutting model framework can show a good fitting effect on the data without deep processing and noise reduction, and the performance is balanced in all sections of semi-rigid asphalt pavement. The application effect of R-F rutting model framework is better than the modified Burgers model framework and the modification of Chinese JTG D50-2017.

The R-F rutting model framework reflects the advantages of fewer characteristic variables and standardized structure, which is easily be popularized and improved. Compared with other constitutive models and mechanical-empirical models, this model framework also has the advantage of easy parameter fitting, and it has higher practical value in the case of rough and incomplete data.

Through the research in this paper, it can be inferred that under the comprehensive environmental conditions of the RIOHTRACK full-scale track, the correlation between rutting depth and temperature factors is small, or the temperature needs to reach a certain threshold to affect the rutting evolution of semi-rigid asphalt pavement. Based on the basic framework of R-F model and the works of predecessors [34, 35], the author will further carry out research, demonstration and improvement under other space-time pavement environment conditions, and the auxiliary study of R-F model is considered through time series analysis. The influence of semi-rigid base on the rutting evolution will be further discussed. Data errors are reflected in measurement, transmission and noise, which have an important impact on research. The denoising and exception processing of data are complicated and will also be further studied in the follow-up work.

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Conflict of interest

The authors declare there is no conflict of interest.

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