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Construction of Data-Driven Explicit Rutting Evolution Model for Asphalt Pavement

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How To Cite: Kou, B.; Cao, J.; Shi, Z.; et al. Construction of Data-Driven Explicit Rutting Evolution Model for Asphalt Pavement. *Applied Mathematics and Statistics* **2025**, *2*(2), 5. https://doi.org/10.53941/ams.2025.100005.

Received: 26 June 2025
Revised: 9 July 2025
Accepted: 11 July 2025
Published: 18 July 2025

Abstract: Rutting is a non-stationary complex process, and its research has been the focus and difficulty in the world and industry for a long time. Effectively revealing the evolution law of asphalt rutting will play a positive role in optimizing road design, preventive maintenance and resource saving, which will help promote the development of transportation infrastructure to a more environmentally friendly and low-carbon direction. How to capture the temporal and spatial evolution law of rutting and express it through an explicit model will greatly improve the research level of permanent damage of asphalt pavement, which is the research difficulty of the industry and also the focus of this paper. In this paper, RIOHTrack was used to measure the database of more than 100 million loads of full-scale ring road. Time series method was used to overlay the original Kou&Cao model framework proposed by our team, and an explicit model framework was proposed here, which can well present the linear and nonlinear process of rutting evolution in time and space. The model framework perfectly fits the process of rutting, the fitting accuracy reaches 0.993 when tested on seven kinds of pavement structure data. The rolling prediction accuracy reaches 0.972. The proposed model framework effectively improves the interpretability of the asphalt rutting evolution model, greatly improves the accuracy of the asphalt rutting evolution model, and has excellent generalization ability, which is closer to revealing the real situation of the temporal and spatial evolution of asphalt pavement, and plays an important role in the study of the long life of asphalt pavement.

Keywords: rutting; asphalt pavement; data-driven; prediction; RIOHTrack

1. Introduction

The study of service performance evolution of asphalt pavement is an important premise to ensure the service and durability of asphalt pavement, and it has important significance for pavement design and maintenance decisions. Its research can further play a positive role in optimizing road design, preventive maintenance, and resource conservation, effectively support environmental protection and energy conservation, and further help human sustainable development.

The literature [1] pointed out that fatigue damage is an important cause of pavement performance failure. Rutting is one of the key indexes to evaluate pavement performance and fatigue damage, so it is very important to study rutting deeply. Exploring the temporal and spatial evolution of rutting is also the main research content of this paper. Refs. [2,3] pointed out that it is helpful to make a more accurate and more scientific maintenance and repair plan. By understanding the rutting formation mechanism and influencing factors, it can provide a scientific basis for the design and ratio of asphalt mixture, reduce the occurrence of rutting disease by optimizing the material properties and structural design. Effective research on rutting can reduce road surface diseases, improve smoothness and stability, and then improve driving safety. Reducing the occurrence of rutting can significantly reduce the cost of road maintenance and reconstruction, and further save energy. With the increase of global climate change and extreme weather events, the environmental challenges faced by asphalt pavement are becoming increasingly severe.

Since the 1960s, scholars from various countries have begun to conduct systematic scientific research on the permanent deformation of asphalt pavements. In 1972, at the Third International Conference on Asphalt Pavement Structure Design, Barksdale and Romain proposed the layer strain method to predict rutting of flexible pavements [4]. In 1987, at the Sixth International Conference on Asphalt Pavement Structure Design, Eisenmann and Hlilmer pointed out that the main cause of initial rutting was the compaction deformation of the mixture, and the main cause of later rutting was the shear push and flow of the mixture [5]. In 2000, Tarvey conducted experiments on the frequency surface of asphalt pavements and concluded that the shear characteristics of asphalt pavements were nonlinear [6]. In 2006, at the Tenth International Conference on Asphalt Pavement Design, Humvey and Monisith conducted experimental studies on rutting of asphalt pavements under different wheel loads, wheel pressures and temperatures, obtained the experimental section profiles, and found obvious shear deformation at the wheel-rail edge. Based on the experiments, they established a correct rut prediction method to evaluate the shear resistance performance of the mixture [7]. Under high-temperature conditions, asphalt mixtures exhibit three properties: adhesion, elasticity and plasticity, and are more likely to produce irreversible permanent deformation.

One of the key obstacles in researching related models is the lack of data on rutting evolution under standard axle load levels that meet the requirements of the entire life cycle. Since the Dutch East Indies Road Association built a full-scale test road in 1920, full-scale accelerated loading tests have undergone a development process of over a hundred years, playing an important role in improving the pavement design system, perfecting design models and indicators, and enhancing design reliability [8]. The AASHO test loop completed in 1959 effectively supported the birth of the world-renowned AASHO Road Design Guide, and in 1984, France conducted accelerated loading tests on the Nantes Ring Road, continuously verifying and improving the French road design method [9,10]. The outdoor accelerated loading tests in South Africa have achieved influential research results through the study of relevant structures of semi-rigid base asphalt pavements [11]. In the 1950s, the United States began to study long-life asphalt pavements and defined the lifespan of long-life pavements as 50 years or more, but up to now, there is still no complete long-life design method system.

Although with the development of technologies such as artificial intelligence, the accuracy of models has become increasingly precise, the non-explicit nature of the models limits their contribution to engineering design and implementation. Therefore, the study of display models is indispensable.The Kou&Cao explicit rutting prediction model proposed by [12] has a good effect to capture the non-stationary evolution trend of rutting. Based on the research application of author [13], the research of this paper reflects the extraordinary value of the ARIMA model in capturing seasonal change rules and rutting evolution mechanisms, and greatly improves the explainability and practical significance of the explicit model. The fitting accuracy is close to or even exceeds that of some verified machine learning models. Compared with other explicit model methods, the prediction accuracy has achieved the best results.

Scholars around the world have carried out a large number of accelerated loading or test road section studies, but the road life obtained by these means is short, and most of them cannot cover the whole life process [14]. At the same time, loading times of most test data are less, which is far from meeting the requirements of loading times of the whole life cycle. In addition, most of the existing accelerated loading tests are carried out at a specific temperature and the environment is fixed, which cannot truly simulate the actual environmental factors. In addition, the axle load of the test is relatively simple, and the research and data requirements on complex factors are quite different. The development of the full-scale road came into being, and the research of [15, 16] elaborated the importance and development process of it.

The research in this paper is based on more than 100 million axle load data of the advanced RIOHTrack full-scale ring road in nearly 8 years, covering valuable data of rutting evolution, such as structure, axle load, temperature, humidity, air pressure, radiation, etc. This paper presents an explicit rutting evolution model suitable for fitting the rutting process and multi-step prediction. On the basis of improving the model's accuracy and generalization ability, multi-step prediction is achieved. Compared with mainstream machine learning models under the same data conditions, it can also have better prediction results. The model adopts data-driven method, coupling time series with Kou&Cao model, which greatly improves the accuracy and interpretability of rutting prediction model, and integrates the characteristics of time and space evolution of rut evolution. The model tested seven kinds of pavement structure data, and the highest fitting accuracy was 0.993, and the highest rolling prediction accuracy was 0.972. The proposed model framework greatly improves the accuracy of the asphalt rutting evolution model, has excellent generalization ability, and is closer to revealing the true meaning of the space-time evolution of asphalt rutting.

Based on the above introduction, Section 2 further introduces the loading data, Section 3 introduces the model structure, Section 4 is the simulation and comparison, and Section 5 is the summary and prospect of related content.

2. Data Structure

The research of this project relies on the data of RIOHTrack full-scale ring road, which is obtained from the actual road surface loading. Researchers in the reference [15,17] elaborated the structure of RIOHTrack full-scale ring road, located in Tongzhou District of Beijing, the foot Ring Road is 2,038 meters long and 3.75 meters wide, with an initial investment of hundreds of millions of yuan, covering 19 different forms of mainstream structural asphalt pavement. Since its completion in November 2015 and the official loading operation in December 2016, it has lasted nearly 8 years of non-stop loading, and has collected more than 100 million valuable loading and environmental data.

RIOHTrack full-scale ring road, covering seven structural forms, 19 kinds of pavement, including 12cm AC and 16-18cm AC semi-rigid base structure, rigid composite and flip base structure, asphalt concrete structure I and II, full thickness structure. The soil foundation design modulus of all kinds of structures is 40 MPa, and the pavement structure is shown as follows Figure 1.

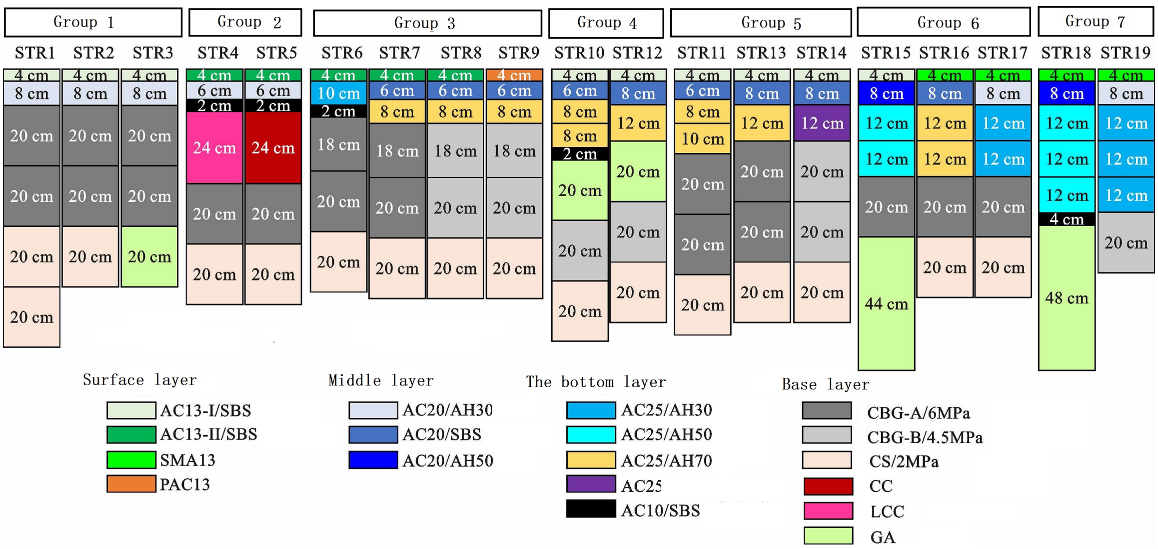

Figure 1. According to the different types of pavement structure, it is divided into seven kinds of pavement structure, 19 kinds of pavement data content.

In this paper, the measured full-scale ring road data of seven structural asphalt pavements are processed by weighted average of different pavements. In this way, the influence of data anomalies caused by data transmission on the evolution law can be effectively reduced, and the robustness of the model can be improved. In this paper, a noise reduction method based on adaptive white noise Empirical Mode decomposition (CEEMDAN) and wavelet packet adaptive threshold can serve as the tool of model construction and comparison analysis, which has been proved effective by [18]. The evolution of seven structural road ruts with the loading data is as follows:

As shown in Figure 2, rutting evolution curves and statistical distribution of pavement with different structures are different. Secondly, rutting depth gradually rises when axle loads increase. The maximum value of the vehicle appears in the summer high temperature every year, and the ruts gradually decrease with the decrease of the temperature. From the evolutionary data, the rutting of asphalt pavement has a significant correlation with the structure, axle load times and temperature factors. However, in the actual data-driven explicit model construction process, it is impossible to introduce all the major external factors, which reduces the practical significance and interpretability of model parameters to a certain extent. Therefore, it is particularly valuable to build an interpretable model that integrates all the factors.

During the construction of the rutting model, features were selected from the RIOHTrack full-scale circular track data. Finally, two features, namely the axle load frequency and the pavement structure, were chosen as the basis for constructing the rutting evolution model [12]. Through the feature selection method, the correlation between the data features and the rutting evolution was analyzed. The literature [19] conducted a detailed assessment of the generalization ability of the feature selection for the rutting evolution model construction.

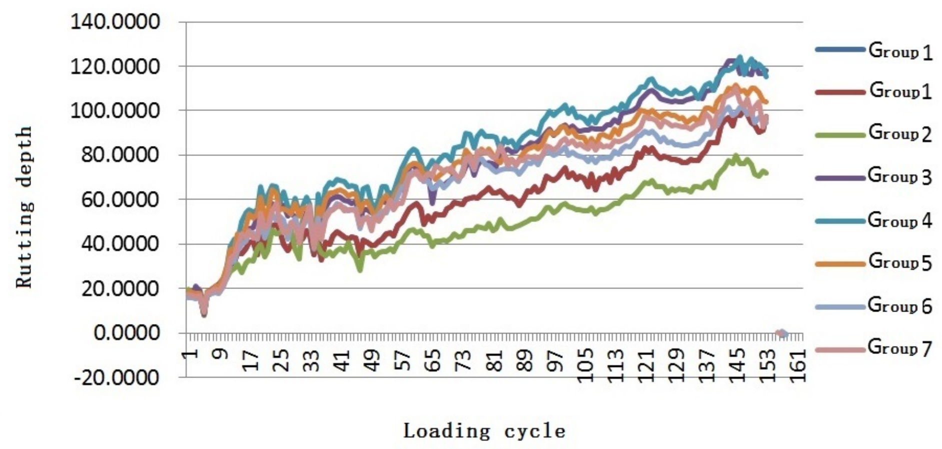

Figure 2. Rutting evolution process under standard axle load for 100 million times on seven road surfaces.

After eight years of more than 100 million loads of asphalt ruts, fruitful data and theoretical results have been obtained. According to the conversion model of standard axle load times and asphalt pavement life, the current pavement life is equivalent to 30 years, which has reached the international advanced level.

On the basis of the above data, combined with the time series, mechanics and empirical theory, the paper proposes model framework here for the first time.

3. Model Framework

Explicit models are based on clear mathematical equations or physical laws, and the problems are directly solved through analytical methods or numerical calculations. The concept and techniques of explicit models have undergone decades of research and practice, and have formed a complete theoretical system and methods. The construction of explicit models relies on multiple-objective nonlinear material evolution coupling, comprehensive factor representation of the complex real environment, long data evolution cycles and large data scales, etc. Compared with the implicit models, they have the characteristics of clear theoretical structure and strong interpretability, especially in the engineering field, where they can better guide engineering design, form norms and standards.

The rutting evolution data used in this study covers rut, temperature, humidity and other data under standard axle load 100 million times, but the data fluctuates greatly and is not stable. In order to better integrate time series model methods, how to effectively extract the nonlinear main trend of data evolution and how or whether to obtain the effective data of stationarity are particularly critical for time series modeling.

The purpose of this paper is to construct an explicit rutting evolution model framework for asphalt pavement so as to effectively characterize its evolution scale. Therefore, based on the research results of our team and superimposed ARIMA model, Kou&Cao-ARIMA model framework of this paper is proposed. Besides the accuracy, the model also has the characteristics of strong generalization ability. The full-scale track data of RIOHTrack was analyzed using the random forest method, and finally two features were selected as the basis for model construction [12].

3.1. Kou&Cao Model Framework

Through literature research and data demonstration, this rutting model frame can excavate the main structure of asphalt pavement. By effectively selecting the correlation features, the generalization ability of the model can be improved. Reference [19] have demonstrated and analyzed this, and the model framework in this section is also built on this basis.

This model framework was first proposed by [12], which effectively characterized the nonlinear relationship between rutting and axle load on asphalt pavement, as follows,

$$RD_i = \lambda + \sum_{k=1}^{5}(\alpha_k N_s^k + \beta_k N_s^{-k}). \tag{1}$$

where,

RD_i is the rutting depth;

i, here is the number of layers;

a_k, λ, α_k and β_k are coefficients;

N_s is the logarithm of the number of loads.

This model is the latest research result, and has shown excellent fitting effect in the literature. The model is clearly expressed and has strong generalization ability. Compared with the existing mainstream explicit models, this model shows better fitting accuracy, which is shown in Table 1.

Table 1. Rut fitting effect of seven types of structural pavement.

Statistics/Groups	1	2	3	4	5	6	7
R^2	0.967	0.917	0.976	0.974	0.973	0.973	0.975
RMSE	3.066	3.550	3.617	3.945	3.472	3.197	3.374
SSE	1184.72	1587.95	1648.299	1961.294	1519.236	1287.77	1434.613

According to the previous research and demonstration, this model has the potential and ability to capture the nonlinear process of rutting evolution, so this paper jointly constructs the displayed rutting prediction model.

3.2. Stationarity Test

After obtaining the trend term of rutting evolution through the above model, whether the data with the trend term removed is stationarity or not is the key to whether the time series method is applicable. The stationarity testing methods mainly include graph analysis, simple statistics and hypothesis testing. This paper adopts the method of hypothesis testing.

Augmented Dickey-Fuller (ADF) test is one of the most commonly methods to determine the stationarity by checking whether there is a unit root. Reference [20] verifies the effectiveness of ADF unit root method in complex data evolution. In this paper, ADF is used to verify the stationarity of the remaining sequences after trend extraction from Kou&Cao model. If it is not stationary, we further use the difference method to verify its stationarity. If it is stable, it is directly used for model construction, which also inversely verifies the validity and rationality of Kou&Cao model framework.

The construction of this paper assumes the following conditions, that is:

- Null hypothesis: There is a unit root.
- Alternative hypothesis: There is no unit root.

If the null hypothesis (e.g., $p > 0.05$) cannot be rejected and the sequence is not stationary, it is still necessary to test the stationarity of the first-order difference of the sequence.

Through the test and analysis of the data, we find that the data is stable after removing the trend item. This creates conditions for the further construction of time series model, and also proves the effectiveness of trend model.

3.3. The Model Framework of This Paper

If a system's observed value x_t at time t is related not only to its previous observations $x_{t-1}, x_{t-2}, \cdots, x_{t-p}$ but also to its previous perturbations $\epsilon_{t-1}, \epsilon_{t-2}, \cdots, \epsilon_{t-q}$ the perturbations et at time t, then the system is called an autoregressive moving average system. Its basic form is as follows:

$$x_t = \lambda_1 x_{t-1} + \lambda_2 x_{t-2} + \cdots + \lambda_p x_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q}. \tag{2}$$

ARIMA(p, d, q) is called the differential autoregressive moving average model. Through the trend item extraction and stationarity test of data, and the data need to be non-white noise sequence, further modeling can be done. Through the above and further ARIMA model order and parameter estimation, the specific model form is as follows:

$$\begin{aligned} RD_i(t) &= RD_i + X_t \\ &= \lambda + \sum_{k=1}^{5} (\alpha_k N_s^k + \beta_k N_s^{-k}) + ARIMA(p, d, q). \end{aligned} \tag{3}$$

where,

RD_i is a nonlinear trend term;

X_t is the stationary or non-stationary random term;

λ, α, β, p, q, d are model parameters.

According to the stationarity test of the data of each road section in this paper, it is known that the difference number made by the time series to become a stationary time series is zero, that is, $d = 0$, which is the ARMA model. ARMA model combines autoregressive and moving average methods, and has good predictive performance and explanatory ability. After obtaining the parameters of the model, forward prediction can be carried out, and the predicted value can be obtained successively by using the predicted value recursion. The extrapolation prediction of MA(q) and ARMA(p, q) is generally to convert the MA(q) and ARMA(p, q) models into the corresponding higher-order AR models, and then extrapolate the prediction formula of the AR models. The prediction error formula is:

$$\begin{aligned} e_t(l) &= x_{t+l} - \hat{x_t}(l) \\ &= \psi_0 \epsilon_{t+l} + \psi_1 \epsilon_{t+l-1} + \cdots + \psi_{l-1} \epsilon_{l+1}. \end{aligned} \tag{4}$$

The variance of the linear minimum variance prediction is related to the prediction step l, but not to the time origin t of the prediction. The larger the prediction step size l is, the larger the variance of the prediction error is, so the accuracy of the prediction will be reduced.

Remark 1. *The model framework is an important discovery in this field. The model has good interpretability. The structure of the model is clear and the parameter solving speed is fast. Based on the original model proposed by the author team, the time series model is superimposed to effectively capture the non-stationary and stationary information of rut evolution. We are surprised to find that the data is stable after stripping the non-stationary trend term. In this paper, the rolling prediction method is used to improve the model prediction. The model constructed in this paper has all the advantages of explicit model, and significantly improves the prediction accuracy and interpretability of rutting evolution model.*

4. Simulation and Comparison

The simulation data used in this paper is rutting evolution data of RIHOTRrack full-scale ring road from November 2016 to December 2023, with a total of 101.49 million standard loading axles. On the basis of the data, the paper uses CEEMDAN and wavelet packet denoising methods to denoise the data. The data used here covers rutting and axle load data of 19 types of road structures of seven types of RIOHTrack, with a total of 153 loading cycles, and the standard axle load times of 1.09 million every two adjacent time intervals.

4.1. Model Fitting

Seven types of road data are fitted by using the proposed Kou&Cao-ARIMA model frame. Through the work in this section, the fitting effect is verified, the nonlinear trend capturing effect of Kou&Cao is also verified in reverse. The specific steps are as follows:

- Using Kou&Cao model frame and the data after noise removal, the parameters are estimated, and the nonlinear rutting model suitable for various structure pavement is obtained.
- Calculate the residual error after model fitting.
- Calculate the stationarity of residual data and determine whether to use ARMA or ARIMA model for further fitting.
- The time series model is built, and the Kou&Cao model is superimposed to get the final model.

The rutting evolution of seven types of road data was predicted respectively, and the fitting accuracy of all of them was between 0.9934 and 0.973. It shows that the model framework, with more than 100 million loading cycles, can perfectly represent its evolutionary data size effectively by the model in this paper. Because the model frame has a very high fitting effect on all asphalt pavement structures, it reflects the good generalization ability of the model. The specific fitting results are as the following Table 2.

Table 2. Model fitting accuracy of seven types of asphalt pavement.

Statistics/Groups	1	2	3	4	5	6	7
R^2	0.9869	0.9730	0.9910	0.9886	0.9892	0.9894	0.9934
$RMSE$	2.3663	2.4783	2.5970	2.9108	2.4550	2.2269	1.9088
SSE	856.7002	939.7589	1031.9	1296.3	922.1145	758.7323	557.4823

Based on the above data, the constructed model framework is fitted and the differential evolution algorithm is used to obtain the relevant parameter values. The specific results are as the following Table 3.

Table 3. Concrete parameter results that fitted.

Groups	1	2	3	4	5	6	7
λ	2.79×10^{11}	3.53×10^{11}	2.57×10^{11}	5.73×10^{11}	4.79×10^{11}	3.81×10^{11}	6.18×10^{11}
α_1	-3.64×10^{10}	-4.61×10^{10}	-3.39×10^{10}	-7.52×10^{10}	-6.28×10^{10}	-4.98×10^{10}	-8.12×10^{10}
α_2	3.24×10^{9}	4.12×10^{9}	3.05×10^{9}	6.74×10^{9}	5.63×10^{9}	4.45×10^{9}	7.29×10^{9}
α_3	-1.88×10^{8}	-2.40×10^{8}	-1.79×10^{8}	-3.95×10^{8}	-3.29×10^{8}	-2.60×10^{8}	-4.27×10^{8}
α_4	6.45×10^{6}	8.27×10^{6}	6.21×10^{6}	1.37×10^{7}	1.14×10^{7}	8.94×10^{6}	1.48×10^{7}
α_5	-9.91×10^{4}	-1.28×10^{5}	-9.65×10^{4}	-2.12×10^{5}	-1.76×10^{5}	-1.38×10^{5}	-2.30×10^{5}
β_1	-1.48×10^{12}	-1.86×10^{12}	-1.35×10^{12}	-3.02×10^{12}	-2.52×10^{12}	-2.01×10^{12}	-3.25×10^{12}
β_2	5.35×10^{12}	6.73×10^{12}	4.84×10^{12}	1.08×10^{13}	9.09×10^{12}	7.27×10^{12}	1.17×10^{13}
β_3	-1.26×10^{13}	-1.59×10^{13}	-1.13×10^{13}	-2.55×10^{13}	-2.14×10^{13}	-1.71×10^{13}	-2.74×10^{13}
β_4	1.76×10^{13}	2.21×10^{13}	1.57×10^{13}	3.53×10^{13}	2.96×10^{13}	2.38×10^{13}	3.79×10^{13}
β_5	-1.10×10^{13}	-1.38×10^{13}	-9.70×10^{12}	-2.19×10^{13}	-1.84×10^{13}	-1.48×10^{13}	-2.35×10^{13}
p	3	2	3	3	1	1	1
d	0	0	0	0	0	0	0
q	1	3	1	3	1	1	1
Constant	−0.0001	−0.0002	−0.0002	0.0018	0.0176	0.0208	0.0227
$AR\{1\}$	1.37	1.86	1.21	1.47	0.80	0.82	0.77
$AR\{2\}$	−0.14	−0.92	0.15	−0.21	/	/	/
$AR\{3\}$	−0.35	/	−0.48	−0.37	/	/	/
$MA\{1\}$	−1.00	−1.38	−1.00	−1.43	−0.21	−0.27	−0.31
$MA\{2\}$	/	0.08	/	0.44	/	/	/
$MA\{3\}$	/	0.30	/	-0.01	/	/	/

The measured data verify that the model has excellent fitting effect, and its result is significantly higher than that of other explicit models. The fitting effects are shown in Figures 3–9.

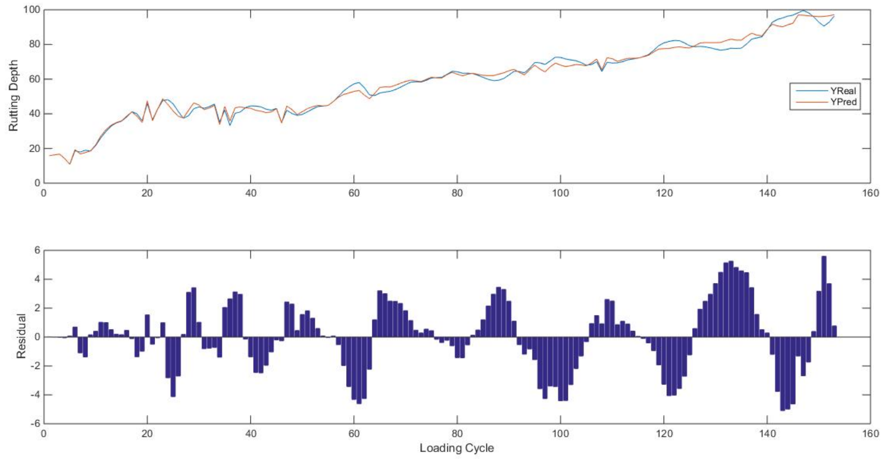

Figure 3. The first group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.987, the RMSE is 2.366, the SSE is 856.7002.

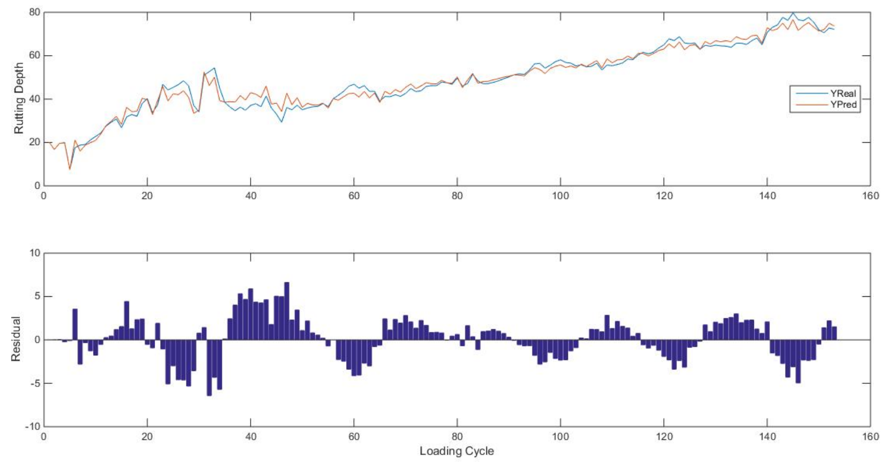

Figure 4. The scend group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.973, the RMSE is 2.478, the SSE is 939.759.

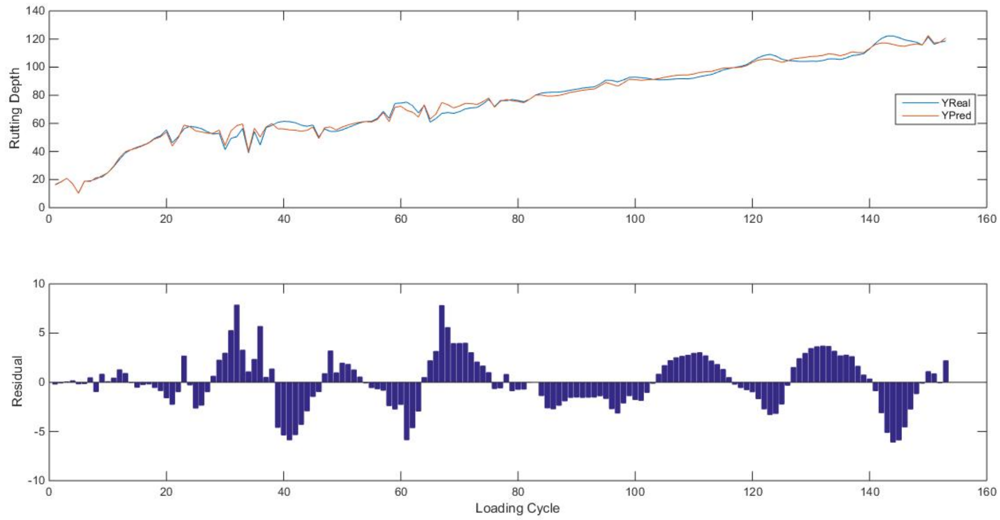

Figure 5. The third group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.991, the RMSE is 2.597, the SSE is 1031.9.

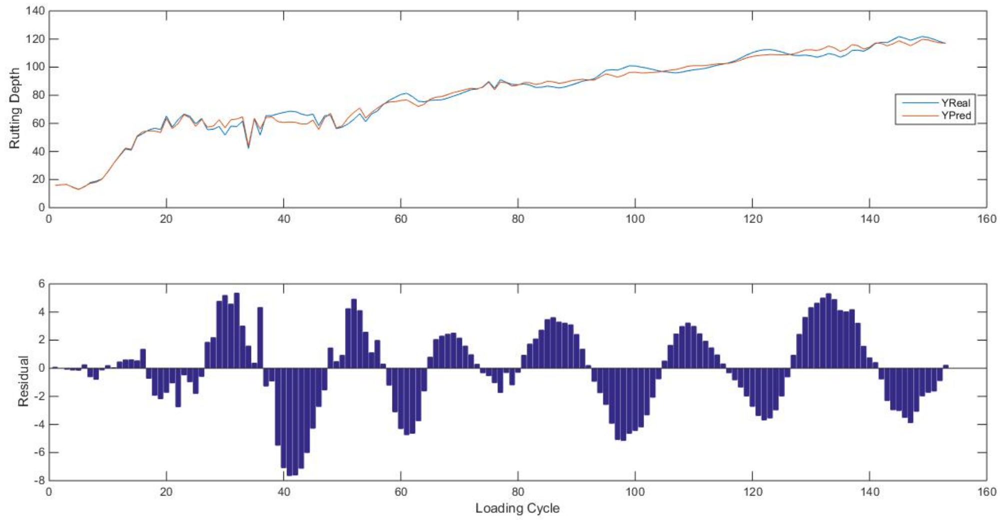

Figure 6. The fourth group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.989, the RMSE is 2.911, the SSE is 1296.3.

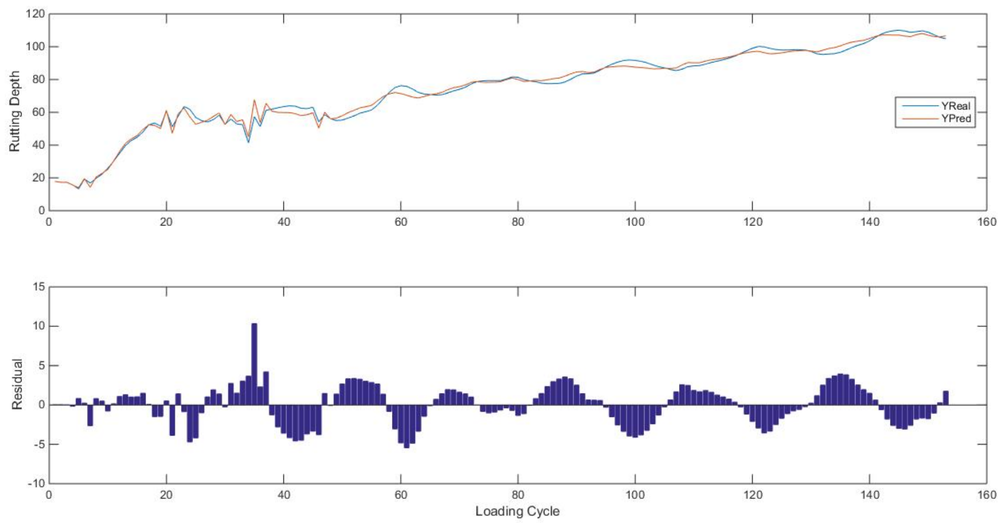

Figure 7. The fifth group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.989, the RMSE is 2.455, the SSE is 922.115.

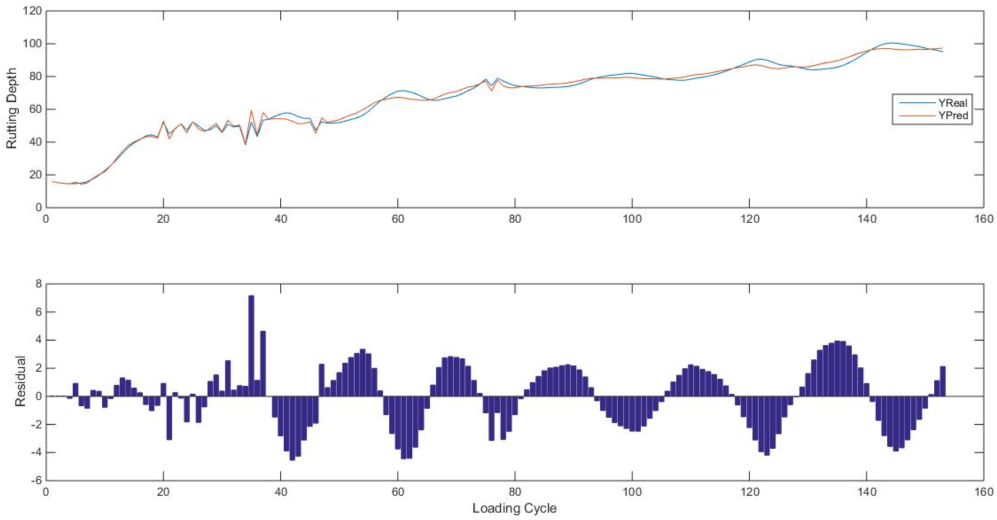

Figure 8. The sixth group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.989, the RMSE is 2.227, the SSE is 758.732.

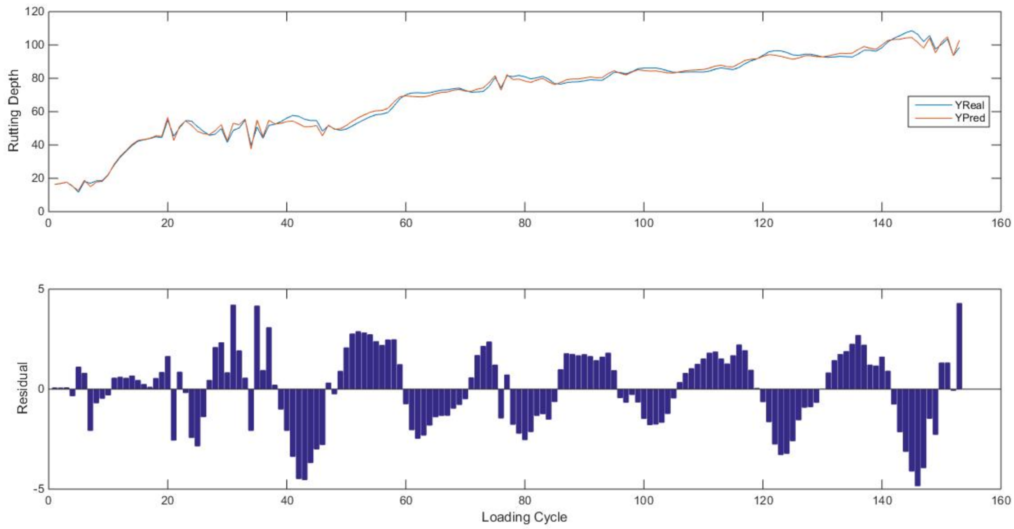

Figure 9. The seventh group of asphalt pavement rutting fitting effect drawings, the fitting accuracy is 0.993, the RMSE is 1.909, the SSE is 557.482.

4.2. Model Prediction

According to the model fitting study, the model has an excellent fitting effect. However, the prediction of rutting evolution is a great test for the model constructed by small sample time series.

This paper improved the one-step prediction of ARIMA by adopting a rolling prediction mode, so that each time point in the test data set participated in iteration, as follows:

- Obtain the nonlinear evolution model and parameters of the training set by using model (1) to predict the trend of the test set.
- Obtain the pre - t time prediction error time series and evaluate its stability.
- Perform ARIMA prediction on the error of $t + 1$ time to obtain the predicted value of the time.
- The above test data is supplemented with the training set data to train new trends and ARIMA models.
- step by step iteration 1$\sim$4 steps, $t + k$, k = 2... Iteratively forecast the test set at all times and complete the prediction of all test sets.

This is essentially an extension of the single-step prediction of the ARIMA model, but the single-step prediction with a period interval of about 1.09 million standard axle loads has significant significance for engineering practice.

In this section, we take the first 80% as the training set and the rest as the test set. The seven groups of data were predicted respectively, and the coefficient of determination of the fitting of the training set was between 0.965 and 0.989, and the coefficient of determination of the prediction effect of the test set was between 0.842 and 0.972. The specific results are as following Table 4.

Table 4. Coefficient of determination of model training set and test set prediction.

Determination/Groups	1	2	3	4	5	6	7
Training	0.985	0.965	0.989	0.977	0.976	0.975	0.969
Test	0.902	0.842	0.922	0.960	0.961	0.972	0.885

The intuitive prediction effects of the specific model are shown in Figures 10–16 .

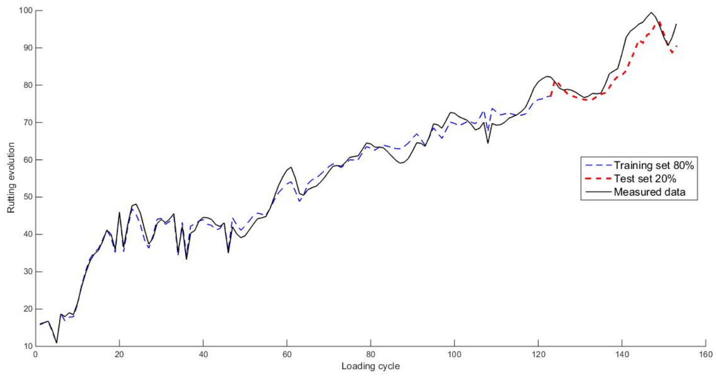

Figure 10. Predictive effects of Group 1's test set and training set.

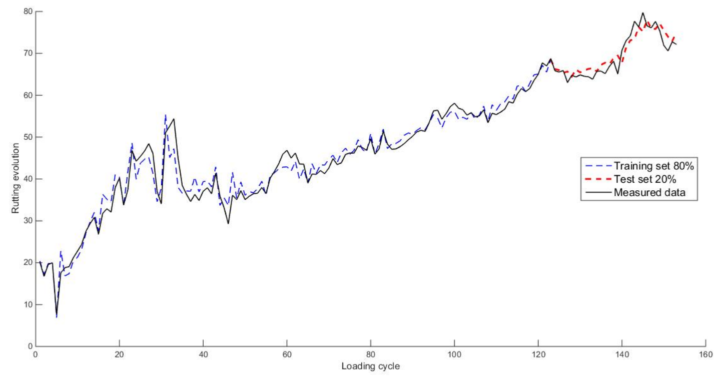

Figure 11. Predictive effects of Group 2's test set and training set.

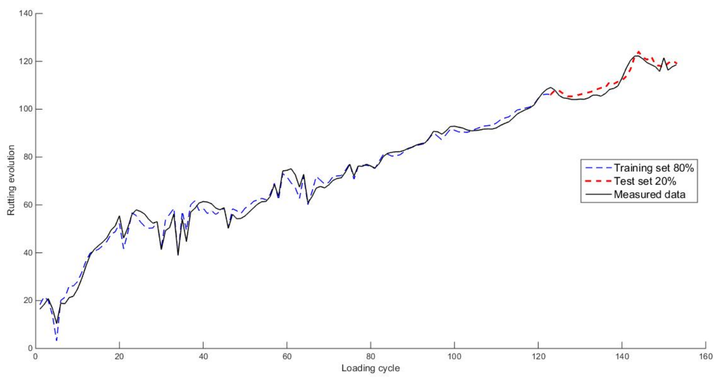

Figure 12. Predictive effects of Group 3's test set and training set.

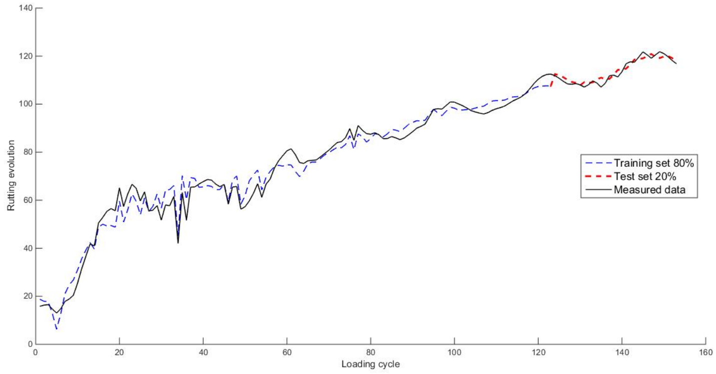

Figure 13. Predictive effects of Group 4's test set and training set.

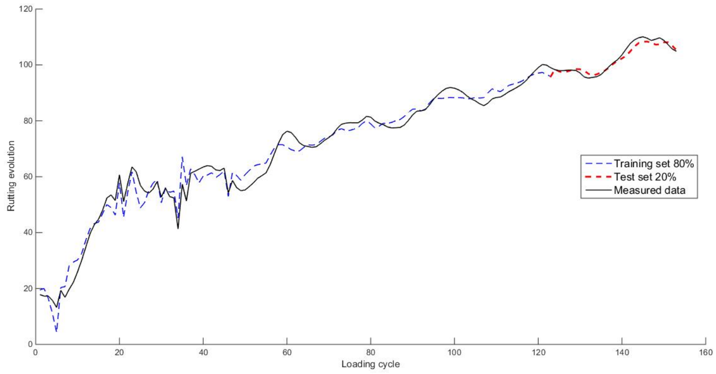

Figure 14. Predictive effects of Group 5's test set and training set.

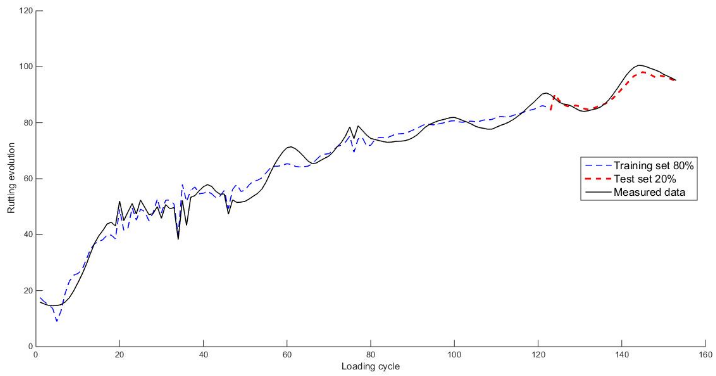

Figure 15. Predictive effects of Group 6's test set and training set.

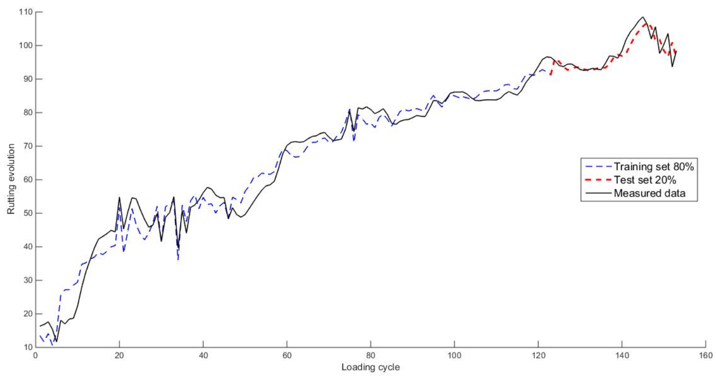

Figure 16. Predictive effects of Group 7's test set and training set.

4.3. Model Comparison

In this paper, an explicit rutting prediction model suitable for all asphalt pavement structures is constructed by time series method superimposed with Kou&Cao nonlinear model. Through data fitting and prediction research verification, the phased model results are obtained. The Burgers model is introduced in detail in Article [21]. It is improved and applied in this section. The JTG D50-2017 model, described in detail in reference [22], has better applicability to the data.

This paper selected mature explicit comparison models for comparison, including Kou&Cao model, improved Burgers (R-B) and JTG D50-2017 specification (R-2017) model, which are introduced as follows:

(1) R-B model, is a nonlinear visco-elasto-plastic model. It can describe the accelerated creep stage of asphalt well.

$$\begin{aligned} RD_{R-B} = 100[\frac{1}{e^{aT}E_1} + \frac{N_s/10000}{e^{bT}\eta_1} + \frac{1}{e^{aT}E_2} \cdot (1 - e^{-\frac{e^{aT}E_2}{e^{bT}\eta_2}}(N_s/10000)) \\ + \frac{\Gamma(\sigma-\sigma_s)}{100e^{bT}\eta_3}(N_s/10000)^n]. \end{aligned} \tag{5}$$

where,

$$\Gamma(\sigma-\sigma_s) = \begin{cases} 0 & \sigma \leq \sigma_s \\ \sigma - \sigma_s & \sigma > \sigma_s \end{cases} \tag{6}$$

σ is the constant stress, σ_s is the yield stress, RD_{R-B} represents the rutting depth under R-B model, N_s represents the cumulative axle load number, a and b are the model coefficients, T is the external environment temperature, E_1 represents the elastic modulus of the Kelvin model, η_1 represents the viscosity coefficient of the Kelvin model in this prediction model, E_2 represents the elastic modulus of the Maxwell model, η_2 represents the viscosity coefficient of the Maxwell model in this prediction model, and η_3 represents the viscosity coefficient.

(2) R-2017 model, is obtained by using RIOHTrack data to modify parameters of the rutting model in the specification JTG D50-2017. The rutting prediction model of Formula (7) is as follows:

$$RD_{R-2017} = a{T_{pef}}^b {P_i}^c {N_{e3}}^d R_{oi}. \tag{7}$$

where, T_{pef} represents the equivalent temperature of the asphalt layer under permanent deformation, P_i represents the vertical compressive stress of the top surface of the asphalt mixture layer i, N_{e3} represents the cumulative acting times of the design lane to reach the design service life, R_{oi} represents the pressure, a, b, c and d are the regression coefficients.

Using the latest rutting loading data, by introducing and comparing the above model, the first group of data is selected as the research comparison data to start the work in this section. Model fitting is the basis for testing the model. The fitting effect is analyzed, and the specific effect parameters are as the following Table 5.

Through the above data research, compared with the relevant models, the model proposed in this paper has achieved excellent fitting effect, the specific details can be found in Table 6. The model constructed in this paper can capture the non-stationary trend under the condition of its nonlinear and non-stationary characteristics, and introduce time series method to achieve better research results through rolling prediction.

The model construction of time series superposition enables the model to supplement the rolling prediction mechanism on the basis of explicit expression, and greatly improves the fitting and prediction ability of the model.

Compared to previous studies, the predictive effect of this model is much higher than that of other explicit models. Ref. [23] trained three deep learning models (RNN, LSTM, and GRU) with different structures and sequence lengths, the results show that the best prediction effect of the deep learning model on RIOHTrack data is R^2 = 0.899, lower than the best prediction effect of the model proposed in this paper.The data of the RNN, LSTM and GRU models were all optimized for pavement structure data through the k-means clustering algorithm. The effect of this model is the average value of all the structural pavement results. The model proposed in this paper has the characteristics of having few input features, clear parameters, and high prediction step size and accuracy.The comparison results are as follows.

Table 5. Comparative analysis of model fitting effect.

Statistics	Kou & Cao-ARIMA	Kou & Cao	R-B	R-2017
R^2	0.987	0.975	0.944	0.938
$RMSE$	2.37	3.25	4.45	5.048
SSE	856.70	1616.43	2688.23	3797.09

Table 6. Comparison with mainstream machine learning models.

Model Types	Training	Test	Prediction Step	Input Features	Parameters Number
Kou&Cao-ARIMA	0.977	0.921	30	2	21
KM-GRU	0.989	0.899	11	32	Unknown
KM-LSTM	0.975	0.813	11	32	Unknown
KM-RNN	0.954	0.773	11	32	Unknown

5. Summary and Outlook

In this paper, Kou&Cao-ARIMA model is proposed innovatively through a data-driven method, which solves the problems of insufficient data mining theory, model accuracy and reliability to a certain extent. The data effect of the model in this paper is significantly higher than that of the existing explicit model, and the fitting and prediction accuracy of ruts of different pavement structures are good, and the maximum values are 0.993 and 0.972, respectively. The model is simple in expression, interpretable and generalization ability, which is conducive to further research and engineering practice, and has significant significance for the study of rutting on asphalt pavement.

How to reveal the true meaning of rutting evolution is the eternal theme of asphalt pavement rutting research, which still needs further bold exploration. In order to continuously optimize the model framework and propose a more effective theoretical framework, the following contents need to be further studied and perfected:

Firstly, the validity of the model framework in this paper is verified on more data sets. Due to the limitation of the measured loading data, it is necessary to expand the validation data set. Secondly, with the deepening of rut loading data, the inflection point mechanism of rut needs to be further explored and demonstrated. At the same time, the study of rutting evolution still needs to strengthen international exchanges and jointly improve the theoretical and research level.

Author Contributions

B.K.: conceptualization, methodology, writing—original draft preparation; J.C.: methodology, writing—reviewing, editing; Z.S.: visualization, data curation; W.H.: conceptualization, supervision; T.M.: software, validation; Y.G.: data curation, software. All authors have read and agreed to the published version of the manuscript.

Funding

This work was supported by the National Key Research and Development Project of China under Grant (No. 2020YFA0714301), the National Natural Science Foundation of China under Grant (No. 61833005) and the Open Project of Key Laboratory of Transport Industry of Comprehensive Transportation Theory (Nanjing Modern Multimodal Transportation Laboratory) under Grant MTF2023004.

Institutional Review Board Statement

Not applicable

Informed Consent Statement

Not applicable

Data Availability Statement

The data that has been used is confidential.

Conflicts of Interest

The authors declare that, there are no known competing financial interests that might affect the work reported in this article.

References

1. Hafeez, I.; Kamal, M.A.; Mirza, M.W.; et al. Laboratory fatigue performance evaluation of different field laid asphalt mixtures. *Constr. Build. Mater.* **2013**, *44*, 792–797.
2. Javilla, B.; Fang, H.; Mo, L.; et al. Test evaluation of rutting performance indicators of asphalt mixtures. *Constr. Build. Mater.* **2017**, *155*, 1215–1223.
3. Coleri, E.; Harvey, J.T.; Yang, K.; et al. A micromechanical approach to investigate asphalt concrete rutting mechanisms. *Constr. Build. Mater.* **2012**, *30*, 36–49.
4. Barksdale, R.D. Laboratory evaluation of rutting in basecourse materials. In Proceedings of the Third International Conference on the Structural Design of Asphalt Pavements, London, UK, 11–15 September 1972.
5. Eisenmann, J.; Hilmer, A. Influence of wheel load and inflation pressure on the rutting effect at asphalt-pavements-experiments and theoretical investigations. *Annu. Rev. Political Sci.* **1987**, *14*, 149–175.
6. Peng, M.J. *Nonlinear Theory and Methods for Rutting Analysis of Asphalt Pavement*; Tongji University: Shanghai, China, 2005.
7. Du, Plessis, L.; Coetzee, N.F.; Hoover, T.P.; et al. Three decades of development and achievements: the heavy vehicle simulator in accelerated pavement testing. In *Pavement Mechanics and Performance*; ASCE: Reston, VA, USA, 2006.
8. Metcalf, J.B. A history of full-scale Accelerated Pavement Testing facilities to 1962. *Road Transp. Res.* **2014**, *23*, 25–40.
9. Banan, M.R.; Hjelmstad, K.D. Neural networks and AASHO road test. *J. Transp. Eng.* **1996**, *122*, 358–366.
10. Tsai, B.W.; Coleri, E.; Harvey, J.T.; et al. Evaluation of AASHTO T324 Hamburg-Wheel track device test. *Constr. Build. Mater.* **2016**, *114*, 248–260.
11. Martin, A.E.; Walubita, L.F.; Hugo, F.; et al. Pavement Response and Rutting for Full-Scale and Scaled APT. *J. Transp. Eng.* **2003**, *129*, 451–461.
12. Kou, B.; Cao, J.; Huang, W.; et al. Rutting prediction model of asphalt pavement based on riohtrack full-scale ring road. *Measurement* **2025**, *242*, 115915.
13. Contreras, J.; Espinola, R.; Nogales, F.J.; et al. Arima models to predict next-day electricity prices. *IEEE Trans. Power Syst.* **2003**, *18*, 1014–1020.
14. Prez, I.; Gallego, J. Rutting prediction of a granular material for base layers of low-traffic roads. *Constr. Build. Mater.* **2010**, *24*, 340–345.
15. Wang, X.D.; Zhang, L.; Zhou, X.Y.; et al. Research progress of RIOHTRACK in china. In *Accelerated Pavement Testing to Transport Infrastructure Innovation*; Springer: Berlin/Heidelberg, Germany, 2020.
16. Priest, A.L.; Timm, D.H. A full-scale pavement structural study for mechanistic-empirical pavement design (with discussion). *J. Assoc. Asph. Paving Technol.* **2005**, *74*, 519–556.
17. Kou, B.; Cao, J.; Huang, W.; et al. The rutting model of semi-rigid asphalt pavement based on RIOHTRACK full-scale track. *Math. Biosci. Eng.* **2023**, *20*, 8124–8145.
18. Guo, Y.; Wang, X.; Wang, S.; Hu, K.; et al. Identification method of coal and coal gangue based on dielectric characteristics. *IEEE Access* **2021**, *9*, 9845–9854.
19. Kou, B.; Cao, J.; Liu, D.; et al. Generalization ability of rutting prediction model for asphalt pavement based on RIOHTrack full-scale track. In Proceedings of the 2024 9th International Conference on Information and Education Innovations, Verbania, Italy, 12–14 April 2024.
20. Khan, I.; Hou, F.; Le H.P. The impact of natural resources, energy consumption, and population growth on environmental quality: fresh evidence from the united states of America. *Sci. Total. Environ.* **2020**, *754*, 142222.
21. Quintanilla, R.; Rajagopal, K.R. On burgers fluids. *Math. Methods Appl. Sci.* **2006**, *29*, 2133–2147.
22. Zhuang, C.; Chen, K.; Ye, Y.; et al. Experimental and computational study on the anti-rutting behavior of an asphalt mixture based on an advanced mts test. *SSRN Electron. J.* **2023**, *18*, e02176.
23. Liu, J.; Cheng, C.; Zheng, C.; et al. Rutting prediction using deep learning for time series modeling and k-means clustering based on RIOHTrack data. *Constr. Build. Mater.* **2023**, *385*, 131515.