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Research Article

Prediction Method of Asphalt Pavement Performance and Corrosion Based on Grey System Theory

Ding-bang Zhang,[1] **Xin Li**,[2] **Yi Zhang**,[3] **and Hang Zhang**[4]

[1] *School of Civil Engineering, Hubei Polytechnic University, Huangshi, China*
[2] *School of Civil Engineering, Changchun Institute of Technology, Changchun, China*
[3] *Civil Engineering Department, Tsinghua university, Beijing, China*
[4] *Chinese Railway Bridge Engineering Bureau Group Company South Engineering Co., Ltd., Guangzhou, China*

Correspondence should be addressed to Ding-bang Zhang; ericzdb@foxmail.com

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The Grey system theory is a new mathematical method to predict data changes in the poor data integrity. As a branch of Grey system theory, the GM (1, 1) model is widely used because only small sample data and simple calculations are needed in prediction of engineering project. It is a critical problem to effectively predict the performance and corrosion of asphalt pavement of highway construction due to the inadequacy of highway performance monitoring data. The smoothness, rut, and pavement skid resistance are three important indexes to evaluate the performance and corrosion of asphalt pavement. This paper has established the prediction model and derived prediction equation of asphalt pavement performance according to the GM (1, 1) model method and then listed the calculation equation of residual and the gray absolute correlation degree. Based on the experience of constructed Dalian-Guangzhou expressway in China, the vectors "a" and "b" in the prediction equation of smoothness, rut, and pavement skid resistance have been calculated by using the original monitoring data. The field monitoring data are compared with the predictive data for residual and the gray absolute correlation. The results reveal that the predicted data of the smoothness, rut, and skid resistance are mostly consistent with the monitoring data, the biggest residual of the above three indexes is smaller than 8.09%, and the gray absolute correlation degrees all exceed 0.9, which means the accuracy of the predicted equation is excellent. The calculation method based on GM (1, 1) model can effectively predict the changing performance index of asphalt pavement.

1. Introduction

The smoothness is an index to evaluate the deviation of the road surface longitudinal concave and convex volume, which reflects the vehicle driving comfort directly. The rut is a long deep track made by the repeated passage of the vehicle wheels; if the rut depth is deep, the road will be impassable. The skid resistance is an index to evaluate the slipper of pavement surface for stopping the typically sideways or oblique of vehicles. The above three indexes all reflect the economy, safety, and working life of a pavement [1–5]. The accurate prediction and evaluation of the above three pavement indexes have an important value, significance, and social benefit for pavement engineering [6, 7]. Therefore, time prediction of the asphalt pavement smoothness, rut, and skid resistance are necessary for improving and controlling the performance of asphalt pavement.

Nowadays, because of the heavy traffic volume, terrible weather, insufficient inspection funds, and other factors, the field monitoring data of the above performance indexes are limited. So some mathematical methods such as probability theory, fuzzy mathematics, and Grey system theory are adopted to predict the changing values of the above performance indexes. But the shortages of probability theory are the large sample size and the main factors of behavioral characteristics are difficult to be found [8, 9]. The fuzzy mathematics is no computation, and fuzzy set transformation is based on "max-min" algorithm and "if ⋯ then" fuzzy logical expert system [10]. The Grey system theory can overcome the deficiency of data shortage on prediction

results; it can make accurate prediction in case of poor data integrity. Especially, as a branch of the Grey system theory, the GM (1, 1) model has the advantages of small sample, high precision, high efficiency, etc. [8, 11].

A comprehensive literature review is conducted to analyze and summarize the studies about asphalt pavement performance [1, 2, 5–7] and Grey system theory [8–15], especially the GM (1, 1) model.

In order to better explore the hazards caused by the reduction of asphalt pavement performance, domestic and foreign scholars have carried out extensive research [5–7]. Dougan C E, Aultman-Hall L., and Choi S. N. et al. [16] had found that the difference in smoothness between lanes is small and consistent (0.1 to 0.2) when averaged over longer sections, and it is not necessary to repeat measurements for all lanes along longer projects or whole routes. JW Li [17] had studied the severity and causes of pavement rut distress and crack distress combining with investigation of an expressway, and the corresponding treatment measures were proposed aiming at pavement distress characteristics. Nataadmadja A. D., Wilson D. J., and Costello S. B. et al. [18] had summarized several laboratory based test methodologies that have been trialled to predict the performance of chip seal surfaces in NZ and the correlation between the laboratory and in-field test results and discussed the advantages and disadvantages of these methodologies. TP Treatments [19] had studied the influence of moisture (wet or dry climate), temperature (freeze or no-freeze zone), subgrade type (fine grained or coarse grained), and traffic loading (low or high) to the pavement performance and put forward the maintenance measures of asphalt pavement about the above factors.

In 1989, Deng Julong [8, 20] had put forward the Grey system theory. The Grey system theory is a system that contains both known and unknown information, which focuses on the problem of "small sample" and "data deficiency". As a branch of the Grey system theory, the GM (1, 1) model is a dynamic model to reveal the development of things and to predict their future development, which is based on the differential equation established by the original data.

Nowadays the Grey system theory, especially the GM (1, 1) model, is widely used in various fields, and the application in the civil engineering is more and more prominent. Liu Junyong [12] made use of the gray GM (1, 1) model to predict the settlement of the roadbed, and the predicted result was accurate, by comparing with monitoring data. Xia Yuanyou [13] studied the change of landslide by using the Grey system theory prediction model, and the reliability of the gray modeling theory in landslide prediction has been verified which played a guiding role in preventing landslide accident. Hu Qingguo [14] used the gray prediction model to predict the deformation of foundation pit accurately, which is very important for the safety construction of foundation pit. Zou Baoping [15] used GM (1, 1) model to predict the seepage flow of seabed tunnel accurately, and the reference for scientific and rational determination of seepage flow has been provided.

According to the literature review, it can be conducted that there are some problems in the current research: (1) many scholars have studied the influences of smoothness, rut, and skid resistance on asphalt pavement. But during the pavement working life, the changing performance of asphalt pavement about the above three indexes is difficult to predict and evaluate. (2) The application of GM (1, 1) model is used in many engineering project, but no scholar has used the GM (1, 1) model to predict the performance index (smoothness, rut, and skid resistance).

Therefore, firstly, this paper aims to establish a prediction model and equations for the smoothness, rut, skid resistance of asphalt pavement by using the GM (1, 1) model method. Secondly, the predicting equations are adopted to predict the changing characteristic of above three indexes of Dalian-Guangzhou expressway in China, respectively. Thirdly, the field monitoring data are compared with the predicted data for residual and the gray absolute correlation, and then the accuracy of the method can be evaluated.

2. Prediction of Asphalt Pavement Performance

The prediction process of the GM (1, 1) model based method is as follows. Firstly, the existing data is processed and optimized to generate a new sequence. Secondly, we use the new sequence to generate a time function. Thirdly, predicting the future elements by using the time function and the changing rule of leading factors and the trend of future development would be revealed. Fourthly, we calculate the residual and the gray absolute correlation degree to evaluate the predicting accuracy.

2.1. Prediction Model Establishment. Let the original data sequence be denoted by

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\right\} \tag{1}$$

where $x^{(0)}(\mathrm{k}) \geq 0$, $\mathrm{k} = 1, 2, 3 \cdots n$, k is the time serial number, n is the total number of monitoring data, and $x^{(0)}(\mathrm{k})$ is the value of the pavement performance index (smoothness, rut, and skid resistance) in the No. k time according to the field monitoring.

Then the 1-AGO (accumulated generation operation) sequence can be obtained as follows:

$$X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right\} \tag{2}$$

where

$$\mathrm{x}^{(1)}(k) = \sum_{i=1}^{k} x^{(1)}(k), \quad k = 1, 2, \ldots, n \tag{3}$$

The sequence $Z^{(1)}$ can be obtained as follows:

$$Z^{(1)} = \left\{\mathrm{z}^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right\} \tag{4}$$

where

$$z^{(1)}(\mathrm{k}) = \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k-1)\right], \quad k = 2, 3, \ldots, n \tag{5}$$

Table 1: Classification of relevance degree.

Accuracy lever	Excellent	Good	Qualified	Unqualified
Absolute relevance ξ	>0.90	$0.8 < \xi \leq 0.9$	$0.7 < \xi \leq 0.8$	≤0.70

The prediction model of pavement performance indexes can be constructed by establishing a first-order differential equation for $X^{(1)}$ as

$$\frac{dx^{(1)}}{dt} + \mathrm{a}x^{(1)} = b \quad \mathrm{t} \in (0, \infty) \tag{6}$$

where the vectors "a" and "b" of the differential (6) can be obtained by the least squares method as follows:

$$[a, b]^T = \left(B^T B\right)^{-1} B^T Y \tag{7}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2) + x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix} \tag{8}$$

$$Y = \left[\mathrm{x}^{(0)}(2), \mathrm{x}^{(0)}(3), \cdots, \mathrm{x}^{(0)}(n)\right]^T \tag{9}$$

Then the solution of the differential equation (6) can be obtained:

$$\hat{\mathrm{x}}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, \quad k = 1, 2, 3, \ldots, n \tag{10}$$

where $\hat{\mathrm{x}}^{(1)}(k+1)$ is the predicting 1-AGO (accumulated generation operation) sequence.

The prediction equation for the original data series can be obtained according to (10):

$$\hat{\mathrm{x}}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{11}$$

2.2. Accuracy Test

(1) Residual Test. The relative error $\sigma^{(0)}(\mathrm{k})$ and the absolute error $\Delta^{(0)}(\mathrm{k})$ between the initial data $X^{(0)}(\mathrm{k})$ and $\widehat{X}^{(0)}(\mathrm{k})$ can be obtained as follows:

$$\Delta^{(0)}(\mathrm{k}) = X^{(0)}(\mathrm{k}) - \widehat{X}^{(0)}(k), \quad \mathrm{t} = 1, 2, 3, \ldots, n \tag{12}$$

$$\sigma^{(0)}(\mathrm{k}) = \left[\frac{\Delta^{(0)}(\mathrm{k})}{X^{(0)}(k)}\right] \times 100\%, \quad \mathrm{t} = 1, 2, 3, \ldots, n \tag{13}$$

If the relative error $\sigma^{(0)}(\mathrm{k})$ does not exceed 10%, then the accuracy of the predicting results is considered to meet the requirements.

(2) Correlation Test. The gray absolute correlation ξ is defined as follows:

$$\xi = \frac{1 + |S| + \left|\widehat{S}\right|}{1 + |S| + \left|\widehat{S}\right| + \left|\widehat{S} - S\right|} \tag{14}$$

where

$$|S| = \left|\sum_{\mathrm{k}=2}^{n-1}\left[X^{(0)}(k) - X^{(0)}(1) + 0.5\left(X^{(0)}(n) - X^{(0)}(1)\right)\right]\right| \tag{15}$$

$$\left|\widehat{S}\right| = \left|\sum_{\mathrm{k}=2}^{n-1}\left[\widehat{X}^{(0)}(k) - \widehat{X}^{(0)}(1) + 0.5\left(\widehat{X}^{(0)}(n) - \widehat{X}^{(0)}(1)\right)\right]\right| \tag{16}$$

$$\left|\widehat{S} - S\right| = \left|\sum_{\mathrm{k}=2}^{n-1}\left[\left(X^{(0)}(k) - X^{(0)}(1)\right) - \left(\widehat{X}^{(0)}(k) - \widehat{X}^{(0)}(1)\right)\right] + 0.5\left[\left(X^{(0)}(n) - X^{(0)}(1)\right) - \left(\widehat{X}^{(0)}(n) - \widehat{X}^{(0)}(1)\right)\right]\right| \tag{17}$$

The larger the correlation value is, the better the correlation between the predicted results and the original data is; the classification of relevance degree according to the absolute relevance is shown in Table 1.

3. Case Study-Use of Prediction Equation in an Expressway

Dalian-Guangzhou expressway is a Chinese expressway connecting Dalian and Guangzhou. As a branch of Dalian-Guangzhou expressway, Hubei section is the middle section between Beijing and Guangzhou in which the full length is 267 km and the design speed is 100 km /h. Because the topography variations and the traffic volume of Hubei section are relatively large, the pavement performance is prone to damage. This paper analyzes the data of the asphalt pavement smoothness, rut, and skid resistance in the Hubei section of

Table 2: The monitoring value of average smoothness for prediction.

Month	Average smoothness		
	Overtaking lane/mm	Traffic lane/mm	Emergency lane/mm
1	5.6	4.0	4.8
2	6.0	4.2	5.0
3	6.0	4.6	5.4
4	6.2	4.8	5.6
5	6.6	5.0	5.6
6	6.8	5.2	6.0
7	7.2	5.6	6.2

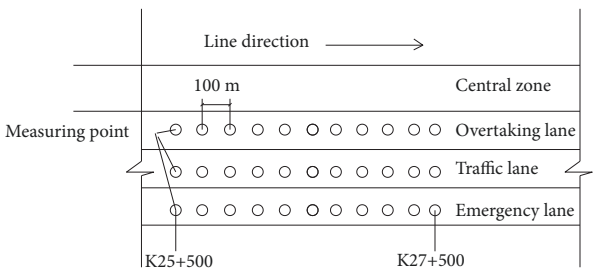


Figure 1: Layout of pavement performance measuring points.

Figure 2: Smoothness measurement.

the Dalian-Guangzhou expressway. Figure 1 shows the layout of pavement performance monitoring points at each lane between the road stake of K26 + 500 and K27 +500 at first month to the seventh month after construction.

3.1. Prediction of Smoothness

3.1.1. Data Collection. According to Highway Detection Specification of China, the smoothness of each lane between K26 + 500 to K55 + 500 of Hubei section is measured by three-meter ruler. Figure 2 shows the smoothness measurement by using the 3-meter straightedge. The frequency of the measuring point is 10 points per 1km, and the average monitoring data for prediction are shown in Table 2.

3.1.2. Prediction and Analysis. The performance prediction model and equation of the pavement are established in Section 2. Taking the data of overtaking lane in Table 2 as an example, the processes of the calculation are as follows.

(1) According to (1) and the monitoring value in Table 2, we can rewrite the original data sequence as

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), x^{(0)}(5), x^{(0)}(6), x^{(0)}(7)\right\} = \{5.6, 6.0, 6.0, 6.2, 6.6, 6.8, 7.2\} \tag{18}$$

(2) After accumulation of $X^{(0)}$, (2) can also be rewritten as follows:

$$X^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), x^{(1)}(4), x^{(1)}(5), x^{(1)}(6), x^{(1)}(7)\right\} = \{5.6, 11.6, 17.6, 23.8, 30.4, 37.2, 42.4\} \tag{19}$$

(3) Combining (4) and (5), the sequence $Z^{(1)}$ can be obtained as follows:

$$Z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), z^{(1)}(4), z^{(1)}(5), z^{(1)}(6), z^{(1)}(7)\right\} = \{8.6, 14.6, 20.7, 27.1, 33.8, 39.8\} \tag{20}$$

(4) Combining (7), (8), and (9), the vectors a and b can be solved by (6):

$$a = -0.04012, \quad b = 5.4993 \tag{21}$$

(5) Then (10) is rewritten as follows:

$$\hat{x}^{(1)}(k+1) = 141.4250e^{0.04012k} - 135.825, \quad k = 1, 2, 3, \ldots, n \tag{22}$$

(6) At last, according to (11), the smoothness prediction equations of overtaking lane can be written as

$$\widehat{X}^{(0)}(\mathrm{k}+1) = 141.4250\left(e^{0.04012\mathrm{k}} - e^{0.04012(k-1)}\right) \tag{23}$$

Similarly, the smoothness prediction equations of traffic lane are

$$\widehat{X}^{(0)}(\mathrm{k}+1) = 79.0207\left(e^{0.0531\mathrm{k}} - e^{0.0531(k-1)}\right) \tag{24}$$

Table 3: The monitoring value and the predictive value of smoothness of each lane.

Month	Overtaking lane		Traffic lane		Emergency lane	
	Monitoring value/mm	Predictive value/mm	Monitoring value/mm	Predictive value/mm	Monitoring value/mm	Predictive value/mm
8	7.5	7.37	6.0	5.93	6.4	6.7
9	7.6	7.67	6.1	6.25	6.8	7.02
10	7.9	7.98	6.5	6.59	7.5	7.34
11	8.2	8.31	7.2	6.95	8.1	7.68
12	8.6	8.65	7.2	7.33	8.2	8.04
13	9.2	9.0	8.0	7.73	8.3	8.41
14	9.3	9.37	8.4	8.15	8.6	8.8
15	9.5	9.75	9.0	8.59	8.8	9.21
16	10.3	10.15	9.5	9.06	9.4	9.63
17	10.7	10.57	9.9	9.56	9.6	10.08
18	10.8	11.0	10.7	10.08	10.2	10.55
19	11.3	11.45	11.0	10.63	10.3	11.03
20	11.6	11.92	11.9	11.21	10.9	11.55

Table 4: Accuracy test results of lane smoothness.

Index		8	9	10	11	12	13	14	15	16	17	18	19	20
Overtaking lane	Residual/%	1.7	0.9	1.0	1.3	0.6	2.2	0.8	2.6	1.5	1.2	1.9	1.3	2.9
	Prediction accuracy	Gray absolute correlation degree $\xi = 0.952$												
Traffic lane	Residual /%	1.2	2.5	1.4	3.5	1.8	3.4	3.0	4.6	4.6	3.4	5.8	3.4	5.8
	Prediction accuracy	Gray absolute correlation degree $\xi = 0.950$												
Emergency lane	Residual /%	4.7	3.2	2.1	5.2	2.0	1.3	2.3	4.7	2.4	5	3.4	7.1	6.0
	Prediction accuracy	Gray absolute correlation degree $\xi = 0.966$												

The smoothness prediction equations of emergency lane are

$$\widehat{X}^{(0)}(\mathrm{k}+1) = 110.2415\left(e^{0.0453\mathrm{k}} - e^{0.0453(k-1)}\right) \quad (25)$$

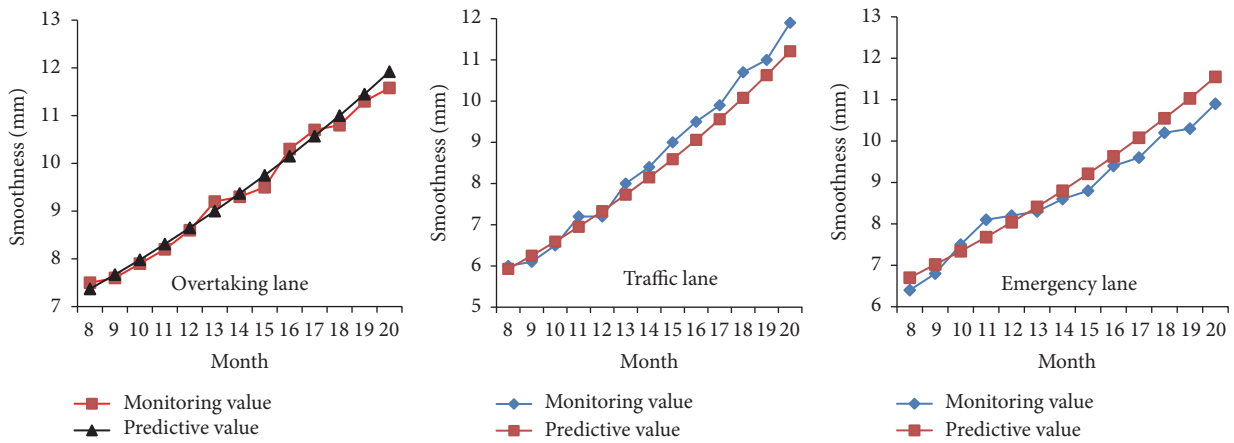
The predicted smoothness of each lane at the eighth month to the twentieth month is calculated by entering equations (23), (24), and (25) and monitoring value in excel software, and the average monitoring values comparing with the predicting values are shown in Table 3. The accuracy test results of each lane's smoothness are shown in Table 4.

Figure 3 shows the monitoring value curve and predictive value curve of each lane's smoothness. It is obvious to find out from Figure 3 that the smoothness of each lane increase with time, and the monitoring values are close to the predictive values. In the overtaking lane, the predictive values are always fluctuating around the monitored values, with an error range of 0.05mm to 0.32mm. In the traffic lane, the predictive values are fluctuating around the monitored values before the thirteenth month; the predictive values are smaller than the monitoring values after the thirteenth month, with an error range of 0.07mm to 0.69mm. In the emergency lane, the predictive values are fluctuating around the monitored values before the twelfth month; the predictive values are bigger than the monitoring values after the twelfth month, with an error range of 0.11mm to 0.73mm.

Table 3 shows the smoothness monitoring values and the predicts of study area. Table 4 shows the accuracy test results of the smoothness on each lane. From Table 4, the residuals of overtaking lane, traffic lane, and emergency lane range from 0.6%-2.9%, 1.2%-5.8%, and 1.3%-7.1%, respectively. The gray absolute correlation degrees of each lane are 0.952, 0.950, and 0.966, respectively, which are calculated by (14), (15), (16), and (17). The average value of the above three gray absolute correlation degree is 0.936 which means the accuracy lever is excellent according to Table 1. The maximum of the gray absolute correlation degree is 0.966 which appears on the emergency lane, and the minimum is 0.950 which appears on the traffic lane. Therefore, the prediction accuracy of emergency lane is the highest and the traffic lane is the lowest because the traffic volume of traffic lane is most heavily of all lanes and the changing characteristics of smoothness of traffic lane are easily affected by heavy traffic. It is concluded that the smoothness of asphalt pavement can be predicted accurately by using the prediction equations (23), (24), and (25).

3.2. Prediction of Rut

3.2.1. Data Collection. According to Highway Detection Specification of China, the study area of this paper is the section K26 + 500 to K55 + 500 of Hubei section. Because the ruts are mainly occurred in the traffic lane, so the traffic lane of the study area is selected to investigate the changing ruts. Figure 4 shows the rut measurement by using the automatic pavement rut tester (APRES) and the 3-meter straightedge.



(a) Smoothness of overtaking lane (b) Smoothness of traffic lane (c) Smoothness of emergency lane

Figure 3: The change curves each lane's smoothness.

(a) Automatic pavement rut tester (b) 3-meter straightedge

Figure 4: Rut measurement.

The frequency of the measuring point is 10 points per 1km, and the average monitoring data for prediction are shown in Table 5.

3.2.2. Prediction and Analysis. The performance prediction model and equation of the pavement are established in Section 3. The value $x^{(0)}(\mathrm{k})$ is obtained from the data between the first month to the seventh month in Table 2, taking (7), (8), and (9) into (10) and (11); then the vectors "a" and "b" can be calculated and the smoothness prediction equations of each lane can be written as follows:

$$\widehat{X}^{(0)}(\mathrm{k}+1) = 202.716\left(e^{0.056\mathrm{k}} - e^{0.056(k-1)}\right) \quad (26)$$

The predicted ruts at the eighth month to the twentieth month are calculated by (26). The monitoring values comparing with the predicting values and the accuracy test results are shown in Table 6.

Figure 5 shows the monitoring value curve and predictive value curve of traffic lane's rut. It is obvious from Figure 5 that the rut is nearly linear growth, and the monitoring values are close to the predictive values. During the eighth month to the sixteenth month, the curve of the monitoring values is fluctuating around the predicting values, and the monitoring values are larger than the predictive values. After the sixteenth month, the curve of the monitoring values is deviate from the curve of the predicting values gradually because of the unpredictable traffic growth, and the monitoring values are

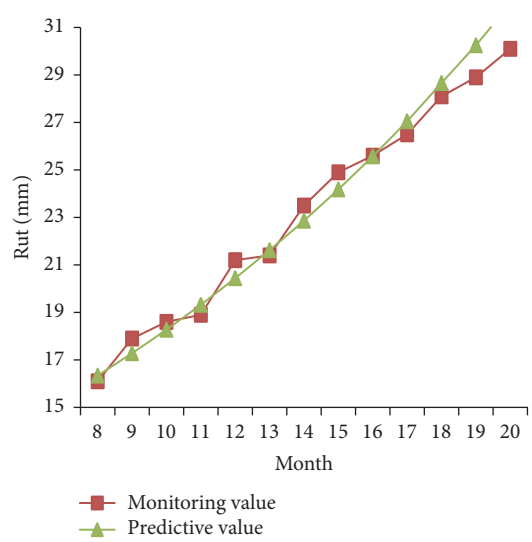


Figure 5: The change curves of rut.

Table 5: The monitoring value of average rut for prediction.

Month	1	2	3	4	5	6	7
Monitoring value of rut/mm	11.6	11.9	12.5	12.9	13.6	14.3	15.9

Table 6: The predictive value and the accuracy test results of rut.

Index	8	9	10	11	12	13	14	15	16	17	18	19	20
Monitoring value/mm	16.1	17.9	18.6	18.9	21.2	21.4	23.5	24.9	25.6	26.5	28.1	28.9	30.1
Predictive value/mm	16.34	17.28	18.27	19.32	20.44	21.62	22.86	24.18	25.57	27.05	28.66	30.25	31.99
Residual/%	1.49	3.46	1.77	2.22	3.58	1.02	2.72	2.89	0.12	2.08	1.99	4.67	6.28
Prediction accuracy	Gray absolute correlation degree $\xi = 0.948$												

Figure 6: Detection vehicle of transverse force coefficient measurement.

smaller than the predicting values; the range of deviation is 0.03-1.89mm.

Table 6 shows the rut predictive values and the accuracy test results of study area. From Table 6, the residuals of traffic lane range from 0.12% to 6.28%, and the maximum residual is 6.28% in the twentieth month. The gray absolute correlation degree of traffic lane is 0.948, which are calculated by (14), (15), (16), and (17). According to Table 1, the accuracy lever is excellent. It is concluded that the rut of asphalt pavement can be predicted accurately by using the prediction equation (26).

3.3. Prediction of Skid Resistance

3.3.1. Data Collection. The skid resistance coefficient is used as the evaluation index to evaluate the antiskid performance of the pavement, the skid resistance is expressed by the transverse force coefficient (SFC) or the tilting instrument (BPN), and the evaluation criteria shall comply with the provisions of the technical specification for highway asphalt pavement maintenance. Because the traffic lane is the main road for vehicles, the changes of skid resistance are more remarkable than the other lane, so the transverse force coefficient (SFC) of traffic lane is chosen to study the skid resistance of traffic lane. Figure 6 shows the detection vehicle for measuring the transverse force coefficient (SFC). The average monitoring values for prediction are shown in Table 7.

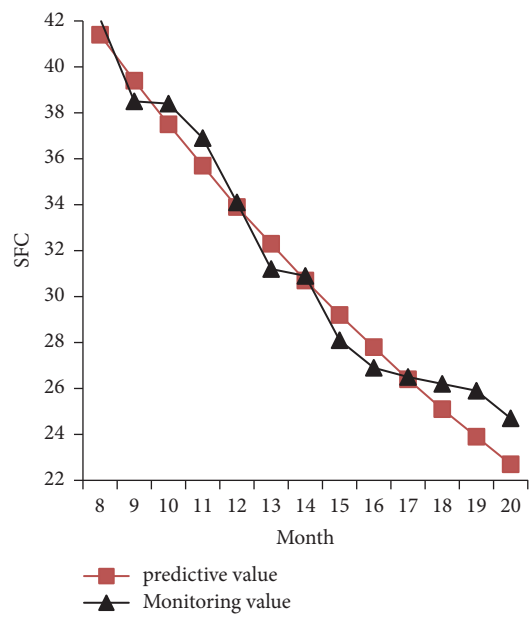


Figure 7: The change curves of SFC.

3.3.2. Prediction and Analysis. The GM (1, 1) prediction model of the pavement's rut is established by the above prediction equations in Section 3. The value $X^{(0)}(1)$ is obtained from the data between the first month to the seventh month in Table 7; taking (7), (8), and (9) into (10), then the skid resistance prediction equation of the traffic lane can be written as

$$\widehat{X}^{(0)}(\mathrm{k}+1) = -1147.2\left(e^{-0.05\mathrm{k}} - e^{-0.05(k-1)}\right) \qquad (27)$$

The predicted SFC at the eighth month to the twentieth month is calculated by (27). The monitoring values comparing with the predicting values and the accuracy test results are shown in Table 8.

The Figure 7 shows the change curves of the monitoring values and the predictive values of the skid resistance (SFC). It is obvious from Figure 7 that the predicted SFC is nearly linear decrease, the curves of the monitoring values are

Table 7: The monitoring value of average SFC for prediction.

Month	1	2	3	4	5	6	7
Monitoring value of SFC	58.4	56.6	53.1	51.9	48.7	47.5	44.8

Table 8: The predictive value and the accuracy test results of skid resistance.

Index	8	9	10	11	12	13	14	15	16	17	18	19	20
Monitoring value	42.1	38.5	38.4	36.9	34.1	31.2	30.9	28.1	26.9	26.5	26.2	25.9	25.7
Predictive value	41.4	39.4	37.5	35.7	33.9	32.3	30.7	29.2	27.8	26.4	25.1	23.9	22.7
Residual/%	1.66	2.33	2.34	3.25	0.59	3.52	0.65	3.91	3.35	0.38	4.2	7.72	8.09
Prediction accuracy	Gray absolute correlation degree $\xi = 0.966$												

fluctuating around the predictive values before the sixteenth month, and the monitored values are close to the predictive values. After the sixteenth month, the difference between the predictive values and monitored values is increasing with time, and the biggest difference is no more than 2.

Table 8 shows the skid resistance (SFC) predictive values and the accuracy test results of study area. From Table 8, the residuals range from 0.59% to 8.09%, and the maximum is 8.09% in the twentieth month. The gray absolute correlation degree is 0.966, which are calculated by (14), (15), (16), and (17). According to Table 1, the accuracy lever is excellent. It is concluded that the rut of asphalt pavement can be predicted accurately by using the prediction equation (27).

4. Conclusion

This paper analyzes the basic principle of gray GM (1, 1) model, establishes the prediction model, and deduces the prediction equation of asphalt pavement performance (smoothness, rut, and skid resistance) and then listed the calculation equation of residual and the gray absolute correlation degree. Based on the experience of constructing Dalian-Guangzhou expressway in China, the prediction accuracy about the above three indexes are studied. The study conclusion shows that the predicted and monitored data of smoothness, rut, and skid resistance are similar and the biggest residual of the three indexes is smaller than 7.1%, 6.28%, and 8.09%, respectively. The smallest gray absolute correlation degree of the above three indexes is bigger than 0.950, 0.948, and 0.966 which means the accuracy of the predicted equation is excellent.

Nomenclature

$x^{(0)}(k)$: The value of the pavement performance index (smoothness, rut, skid resistance) in the No. k time according to the field monitoring
$X^{(1)}$: The 1-AGO (accumulated generation operation) sequence
k: Time serial number
n: The total number of monitoring data
$\hat{x}^{(1)}(k+1)$: The predicting 1-AGO (accumulated generation operation) sequence
$\hat{x}^{(0)}(k+1)$: The prediction equation for the original data series
$\sigma^{(0)}(k)$: Relative error
$\Delta^{(0)}(k)$: Absolute error
ξ: Gray absolute correlation degree
SFC: The transverse force coefficient
BPN: The tilting instrument
"a" and "b": The vectors of the differential equation (4).

Data Availability

The available data are in case study section (Section 3) of this paper. This publication is supported by four datasets, which are openly available at locations cited in the reference section (see [11, 17, 18, 20]).”

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] Z.-F. Lu, Z.-Y. He, and M. Qin, “Pavement performance of asphalt mixture modified by rock asphalt,” *Journal of Central South University (Science and Technology)*, vol. 41, no. 6, pp. 2407–2411, 2010.

[2] T. F. Fwa and K. C. Sinha, “Pavement performance and life-cycle cost analysis,” *Journal of Transportation Engineering*, vol. 117, no. 1, pp. 33–46, 1991.

[3] D.-B. Zhang, Y. Zhang, T. Cheng et al., “Measurement of displacement for open pit to underground mining transition using digital photogrammetry,” *Measurement*, vol. 109, pp. 187–199, 2017.

[4] D. B. Zhang, Y. Zhang, and T. Cheng, “Measurement of grass root reinforcement for copper slag mixed soil using improved shear test apparatus and calculating formulas,” *Measurement*, vol. 118, pp. 14–22, 2018.

[5] Y. Rebekah, "Environmental and economic analyses of recycled asphalt concrete mixtures based on material production and potential performance," *Resources Conservation & Recycling*, vol. 10, no. 4, pp. 141–151, 2015.

[6] H. K. Salama, K. Chatti, and R. W. Lyles, "Effect of heavy multiple axle trucks on flexible pavement damage using in-service pavement performance data," *Journal of Transportation Engineering*, vol. 132, no. 10, pp. 763–770, 2006.

[7] D. Kuttah, "The performance of a trial gravel road under accelerated pavement testing," *Transportation Geotechnics*, vol. 9, pp. 161–174, 2016.

[8] J. L. Deng, "Introduction to Grey system theory," *Sci-Tech Information Services*, vol. 1, pp. 1–24, 1989.

[9] Y. Jing and X. U. Chuan-Sheng, "Mathematical techniques and the development of probability theory," *Journal of Taiyuan University of Technology*, vol. 23, pp. 49–54, 2008.

[10] L. Kaidi and Y. Pang, "Problems and solutions of fuzzy mathematics," *Journal of Hebei University of Engineering*, vol. 4, pp. 106–112, 2011.

[11] L. Lina, *Optimization of Grey GM (1,1) Model and Its Application*, Yanshan University, 2014.

[12] L. Junyong, X. Hui, and D. Wu, "Application of improved gray-model in the settlement prediction of roadbed foundation," *Geotechnical Engineering Technology*, vol. 19, no. 2, pp. 59–68, 2005.

[13] X. Yuanyou, "Grey system forecasting model and its application of landslide," *Journal of Natural Disasters*, vol. 1, no. 12, pp. 74–78, 1995.

[14] H. Qingguo, Z. Keneng, Zhongming, and T. Jia, "The grey prediction model in foundation pit deformation," *Gmining and Metallurgical Engineering*, vol. 26, no. 4, pp. 13–18, 2006.

[15] Z. Baoping and L. Zhanyou, "Prediction of seepage flow of subsea tunnel based on GM model," *China Water Transport (Second Half)*, vol. 16, no. 3, pp. 81–85, 2016.

[16] C. E. Dougan, L. Aultman-Hall, S.-N. Choi, B. Overturf, and C. Hobson, "Variation of pavement smoothness between adjacent lanes: implications for performance-based contracting," *Transportation Research Record*, no. 1860, pp. 152–158, 2003.

[17] J. Li, "Study on survey of bituminous pavement rut distress and patching material performance," *Advanced Materials Research*, vol. 671-674, pp. 1282–1286, 2013.

[18] A. D. Nataadmadja, D. J. Wilson, S. B. Costello, and M. T. Do, "Correlating laboratory test methodologies to measure skid resistance of pavement surfaces," *Transportation Research Record*, vol. 2506, pp. 107–115, 2015.

[19] T. P. Treatments, "Results of long-term pavement performance SPS-3 analysis: preventive maintenance of flexible pavements," *Ltpp Techbrief*, 2011.

[20] D. Julong, "Grey forecast and decision," in *Wuhan*, pp. 108–119, Huazhong University of science and Technology Press, 2002.