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Damage prediction model for concrete pavements in seasonally frozen regions

Модель для прогнозирования повреждений дорожного покрытия в районе сезонного промерзания

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Key words: concrete pavement; damage prediction environmental factor; statistical product and service solution

Ключевые слова: цементно-бетонное покрытие; прогноз состояния повреждения; фактор воздействия на окружающую среду

Abstract. Vehicle loads and environmental differences are the key technical factors in the model construction of concrete pavement damage prediction. According to the data of the 168-month actual number of actions of different vehicle axle types, average temperature, average wind speed, rainfall, snowfall and days below 0 ℃ collected from the Mudanjiang-provincial section of the He-da highway in China, the broken slab ratio of cement concrete (DBL) was calculated. Cracking rate(CRK) and environmental factor(SF) were introduced into the model. This paper uses SPSS analysis method to carry out correlation analysis and partial correlation analysis by introducing SF to the model of DBL and CRK, so that the concrete pavement damage prediction model in seasonally frozen regions can be constructed and tested. Results show that CRK and SF both have positive linear relationship with DBL; Concrete pavement damage in seasonally frozen regions can be predicted by analyzing parameters like actual number of actions of different vehicle axle types, road service time and freezing index, etc. No multiple collinearity exists in the parameters of the model and the construction of model for concrete pavement damage prediction in seasonally frozen regions is of great theoretical significance for timely and effective pavement maintenance. The model has achieved good results in damage prediction accuracy and efficiency.

1. Introduction

After the opening of concrete pavement to withstand the repeated loading of vehicles, under the influence of the climate and material characteristics, the road will gradually appear all kinds of damage. Pavement damage will aggravate or produce derivative diseases over time. The relationship between the prediction of road surface service performance and the prediction of the road damage status established by the law of the development of road disease change is the prediction model of road damage [1–3]. The model can effectively and accurately analyze and evaluate the damage status of pavement in the future. The model can choose and determine the best maintenance plan to prolong the service life of pavement. Therefore, the study on the prediction of pavement damage can provide the theoretical basis and scientific basis for pavement maintenance and decision.

Since the 1950s, domestic and foreign scholars began to study the condition of pavement damage. The obtained research results include deterministic model, probabilistic model [4–6], neural network model [7–9] and so on. In the probabilistic model, various probabilistic models need to rely on experts to score, the subjectivity is strong. The prediction of pavement damage status based on the gray theory model [10–11] can well solve the index problem of complex and fuzzy, but its whitening weight function, the exponent of the evaluation index and the gray clustering coefficient all depend on the empirical range of each index, there are also some subjective experiences. Neural network prediction model has a strong nonlinear fitting ability, and the learning rules are simple, but there are some shortcomings of the model

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itself, which requires sufficient data support, and the reasoning process and reasoning basis are very strict. Zeng Qingxia [12] of Changsha Polytechnic University predicted the damage condition of concrete pavement based on vector machine. The model used machine learning and statistical learning theory and method, the evaluation speed is fast, but there is a lack of consider in diversification and uncertainty of evaluation index influencing factors. Guangdong Province [13] established the PCI deterministic model of pavement condition index by sorting out, analyzing and using empirical methods based on years of accumulated traffic data. However, this model is only an implicit equation of regression coefficient and road age with no consideration of environmental factors. The above results were obtained in the non-seasonally frozen regions, due to the vast territory of our country, the provinces in terms of the number of vehicle axle load, the average temperature, rainfall, snowfall and so on are different, and the road damage status vulnerable to environmental, and traffic and other factors. Combining with the characteristics of climatic environment in seasonally frozen regions, this paper starts with the traffic conditions and environmental factors and establishes a scientific predicting model of the damage condition of concrete pavement.

Based on the field survey data of pavement cracks, environmental factors and the number of vehicle axle loads in He-da highway in China from Mudanjiang to provincial boundary, the paper analyzes the model of pavement cracks and environmental factors in MEPDG, analyzes the model by using SPSS software. SPSS is a "statistical product and service solution" software, the outstanding feature is the use of regression analysis to solve the statistical relationship between a variable and its influencing factors. The relationship between the prediction model of concrete pavement damage in frozen area [14, 15] and the crack model of concrete pavement and the model of environmental factors are also presented to predict the long-term damage of concrete pavement in seasonally frozen regions.

2. Methods

“The Technical Code for Road Maintenance” divides the forms of concrete pavement into the following four types: seams, vertical displacements, cracks and surface damages, and uses the concrete pavement breaking rate (DBL) as the evaluation of pavement damage index. The use of RTM intelligent road test car pavement section of the survey to detect the status of damage. The test car through the image acquisition equipment put the damaged image into high-performance computer, the computer image processing real-time road surface treatment, detection, identification, analysis, and to find out the location and size of cracks in the image on the road, the road crack width measurement accuracy is greater than 1.5 mm, Length measurement accuracy is less than 5 %. In Figure 1, the road age and climatic conditions of Mudanjiang to provincial boundary in He-da highway are the same, but the difference between the survey results of pavement damage on the up and down directions is quite large. The traffic in the up and down directions is different at different sections. When the difference of traffic volume accounts for 3.45 % ~ 6.23 % of the total traffic volume in the surveyed interval, the impact width of pavement cracks is between 8.067 m and 55.681 m. In Figure 2, the traffic volume and road structure of Xu-chang Section National Highway 107 (K759~K775) and Mudanjiang to provincial boundary (K143~K159) in He-da highway are similar. The annual average temperature of the location of He-da highway and Xu-chang Section in National Highway 107 is 6.1 ℃ and 14.5℃, and the width of the pavement cracks is between 64.795 m and 248.937 m.

The above shows that the DBL of concrete pavement shows obvious differences with the traffic load and environmental factors, which provides an important basis for constructing the damage prediction model of traffic and climate impact factors, and makes the model more reasonable.

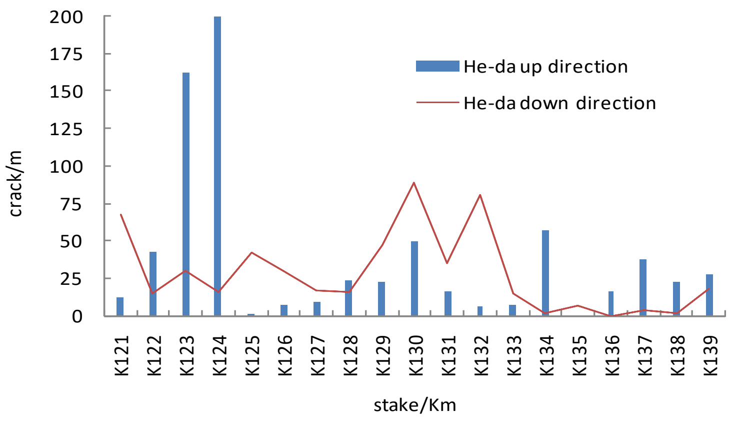

Figure 1. Cracks distribution with mileage in the same section.

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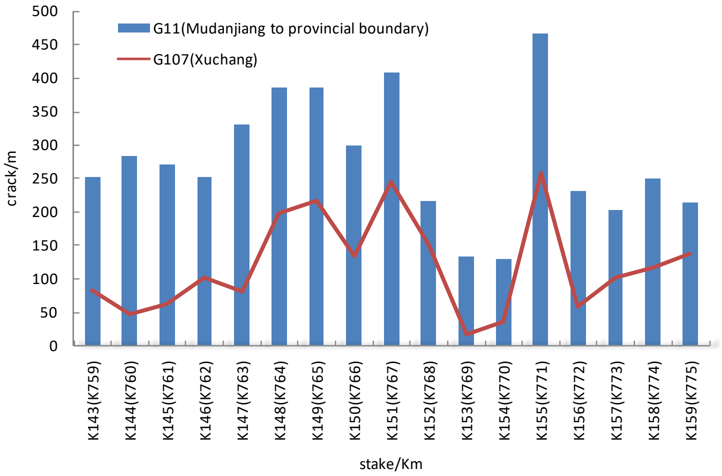

Figure 2. Cracks distribution with mileage in different sections.

Traffic data are obtained by perennial observation of traffic volume, that is, the annual observation time is 365 days and the daily observation time is 24 hours. Because it is difficult to adopt the method of setting up traffic survey stations on the highway to manually calculate the traffic volume of the road sections. Therefore, the use of highway toll stations for road traffic statistics.

The actual number of actions of different vehicle axle types of the survey carried out using the HDS-1-type culvert axle, coal checkpoint, SM2000S axle load automatic detection system and other weight measurement equipment on the actual axle load on the road for 24 hours of full monitoring, classification recorded Survey sections of different shaft weight axis, for summary. Figure 3 shows the traffic volume survey of He-da highway from Mudanjiang to provincial boundary Figure 4 shows the Type I (single shaft, single wheel), type II shaft (single shaft, double wheel on each side), type III shaft (double shaft, double wheel on each side) and IV Type shaft (triple shaft, double wheel on each side) the actual number of times.

Figure 3. He-da highway from Mudanjiang to provincial boundary.

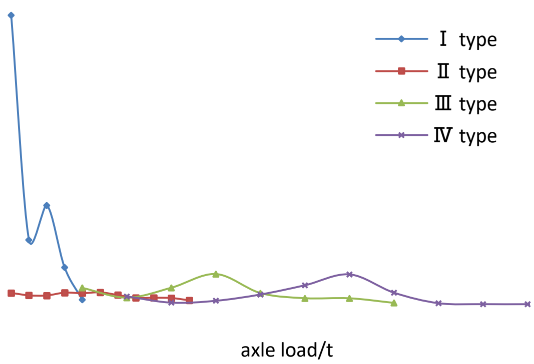

Figure 4. Actual loading times of different vehicles.

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He-da highway where the location of the climate has obvious characteristics of seasonally frozen regions, the climate data comes from 80 meteorological observation stations, and the data of temperature has a total of 168 months from 2003 to 2016. Table 1 shows the survey results of some surveys Data include the temperature of the area under investigation, average wind speed, rainfall, snowfall and the number of days below 0 °C.

Table 1. Road section climate.

year/ month	The highest temperature/℃	Lowest temperature/℃	average temperature/℃	average wind speed /km·h-1	Rainfall /mm	Snowfall /mm	Less than 0 ℃ days /d
2012/1	- 3 °C	- 33 °C	- 20.5 °C	16.05	0	8	31
2012/2	0 °C	- 29 °C	- 16.5 °C	16.75	0	9	28
2012/3	5 °C	- 21 °C	- 7.5 °C	17.15	0	7	31

3. Results and Discussion

Mechanistic-Empirical Pavement Design Guide [16–20] is a research project of AASHO and the National Highway of America, which calculates the stress and strain of pavement structures using traditional mechanics, supplemented by experience Methods to make up for the gap between the indoor test and field test, fully taking into account the characteristics of the pavement materials, pavement traffic conditions and climatic conditions.

CRK (Crack) and SF (Site Factor) are two prediction models based on MEPDG. CRK indicates the proportion of cracks in cement concrete slab. The cracks include horizontal, vertical and diagonal cracks, corner fractures and cross fractures. CRK is a composite function based on DI_F (fatigue damage). Prediction of DI_F is based on Miner's principle of damage accumulation. It is expressed by the ratio of the number of repetitions of traffic load to the number of repetitions of allowed load, as shown in the following formula 1; SF represents environmental impact prediction model, which is a composite function of the age of the material, the freezing index and the passing rate of the roadbed material when the mesh size is 0.075 mm, as shown in Equation 2 below; FI denotes the freezing index, as shown in Equation 3 below.

$$CRK = \frac{1}{1 + DI_F^{\ -1.98}}. \tag{1}$$

$$SF = AGE(1 + 0.5556 * FI)(1 + P_{200}) * 10^{-6} \tag{2}$$

$$FI = \sum_{i=0}^{n} (0 - T_i) \tag{3}$$

Where: DI_F means fatigue damage, AGE means the service life of the road, FI means the freezing index; P_{200} means the passing rate of roadbed material when the mesh size is 0.075 mm; n means the number of days below 0 ℃ and Ti means the average daily temperature.

To characterize the impact of FI on DBL in the environmental impact models of seasonal and non-seasonally frozen regions, the SF comparison between the Mudanjiang to provincial boundary in He-da highway and Xu-chang section in the national highway 107 shown in Figure 5. Seasonal frost-free period throughout the year between 100 to 150 days in seasonally frozen regions, the annual average temperature between -5 °C~9 °C, the climate is significant. From 2003 to 2016, the SF of Mudanjiang to the provincial boundary in He-da highway was $6.13 \times 10^{-3} \sim 86.80 \times 10^{-3}$. From 2003 to 2016, the SF of National Highway107 was $0.48 \times 10^{-3} \sim 6.07 \times 10^{-3}$, the SF of Mudanjiang to the provincial boundary in He-da highway was larger than the SF of Xu-chang Section in national highway 107 10.60 times to 17.84 times, the difference was significant.

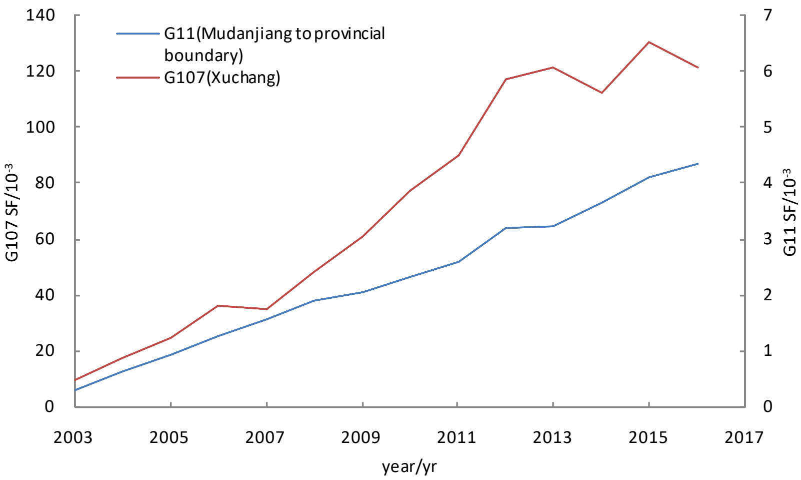

Figure 5. Comparison of *SF*.

Predictive models include two forms. The first type of prediction model is called the direct prediction model, that is, *DBL* and *CRK*, *DBL* and *SF* directly construct the corresponding functional relationship. The second prediction model is to use the *SF* index as a parameter in the *DBL* and *CRK* prediction models. The data model prediction process mainly includes: without introducing other parameter items, fitting the DBL and *CRK*, *DBL* and *SF* respectively according to the distribution of scatter plot to determine the linear or nonlinear relationship; In order to accurately characterize the impact of road age on pavement damage, also in order to reflect the difference caused by the same traffic load but different environmental parameters, introduce *SF* into *DBL* and *CRK* models as a parameter; According to the above results of the fitting hypothesis testing and analysis of model validity and verification, and come to accurate and reasonable prediction model.

Based on the 168-month observation data of traffic volume and environmental parameters collected from the site of Mudanjiang to the provincial boundary in He-da highway and the *CRK* model under MEPDG theory, the cumulative *CRK* of 168-month surveyed road sections was obtained. The *DBL* and the *CRK* of the initial scatter plot fitted to a linear relationship, the logarithmic relationship and the exponential relationship in Figure 6.

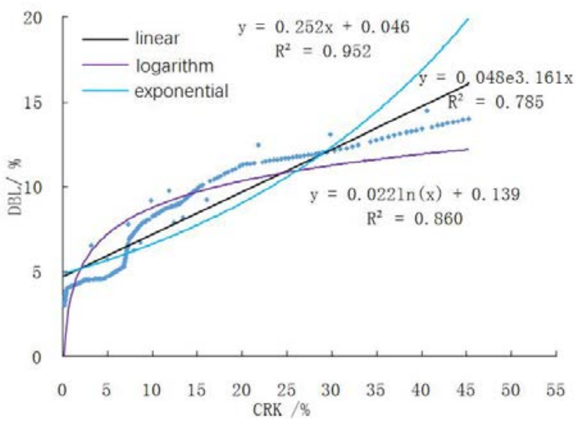

Figure 6. *DBL* and *CRK* fitted curves.

As can be seen from the three regression models in Figure 6, the correlation coefficients of the linear regression, logarithmic regression and exponential regression are 0.952, 0.860 and 0.785, respectively, and the three correlation coefficient values are large, *CRK* and *DBL* is strongly correlated with the previously analyzed. When *CRK* tends to 0, the initial *DBL* value in the linear regression is 0.046, which is obviously smaller than the initial *DBL* values of logarithmic regression and exponential regression, which is consistent with the analysis that basically no cracks occur in concrete pavement. Therefore, considering only the deterministic coefficients obtained from the above regression equations and the reasonableness of fitting results, there should be a linear relationship between *DBL* and *CRK*.

It can be seen from the above analysis that when the same repeated load caused by traffic is present, there is a big difference in pavement damage due to different environmental factors. Therefore, in order to characterize the effect of same traffic load but different environmental factors on the prediction model, the environmental impact factors need to be considered in order to enhance the environmental factors on the damage of pavement. According to the results of fitting, the more reasonable forecasting relation model is obtained. Based on the above mentioned climatic data of the location of He-da Highway, a total of 168 survey data are collected in monthly. Combined with the SF prediction model under MEPDG, the cumulative SF value of 168 months was obtained. The scatter plot between DBL and SF in field survey was initially fitted to a linear, logarithmic and exponential relationship is shown in Figure7.

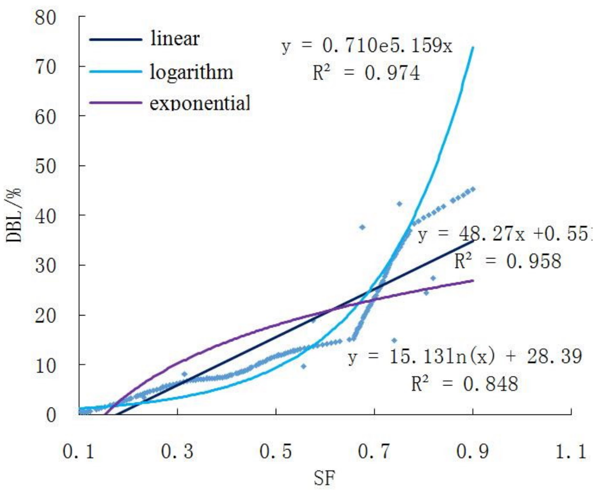

Figure 7. DBL **and** SF **fitted curves.**

As can be seen from the three regression models in Figure 7, the correlation coefficients of linear regression, logarithmic regression and exponential regression were 0.958, 0.848 and 0.974, respectively. Among the three correlation coefficient , the regression coefficient of the exponential model has the largest correlation, indicating that the exponential regression has the strongest correlation. When the SF tends to 0, the minimum initial DBL is 0.551, with just completed the opened concrete pavement basically no crack analysis is also consistent. Therefore, only from the above regression equation can be drawn from the coefficient of determination and reasonable consideration, the linear regression appears to be relatively reasonable.

In order to further verify the correlation among DBL, CRK and SF, SPSS software was used to analyze the correlation between DBL and CRK (Table 2); DBL, CRK and SF (Table 3) were analyzed for partial correlation. In Table 2, CRK and DBL correlation coefficient was 0.944, the significance level was 0.000, less than 0.05, indicating that CRK, DBL correlation was positive, and strong correlation. In Table 3, when DBL was not controlled, the correlation coefficient of CRK and SF was 0.990, the significance level was 0.000 and less than 0.01. When DBL was controlled, the correlation coefficient of CRK and SF was 0.935 and the significance level was 0.000, so CRK, SF and DBL is positive and highly correlated.

Table 2. Correlation of DBL ***and*** CRK.

Control variables		DBL/month	CRK/month
DBL/month	Pearson Correlation	1.000	0.944
	Significance（Bilateral）	—	0.000
	N	168.000	168.000
CRK/month	Pearson Correlation	0.944	1.000
	Significance（Bilateral）	0.000	—
	N	168.000	168.000

Table 3. Partial Correlation of DBL, CRK and SF.

Control variables		*CRK*/Month	*SF*/Month	*DBL*/Month
*CRK/*Month	Pearson Correlation	1.000	0.990	0.944
	Significance（Bilateral）	—	0.000	0.000
	df	0.000	166.000	166.000
SF/Month	Pearson Correlation	0.990	1.000	0.924
	Significance（Bilateral）	0.000	—	0.000
	df	166.000	0.000	166.000
DBL/Month	Pearson Correlation	0.944	0.924	1.000
	Significance（Bilateral）	0.000	0.000	—
	df	166.000	166.000	0.000
*CRK/*Month	Pearson Correlation	1.000	0.935	—
	Significance（Bilateral）	—	0.000	—
	df	0.000	165.000	—
SF/Month	Pearson Correlation	0.935	1.000	—
	Significance（Bilateral）	0.000	—	—
	df	165.000	0.000	—

3.1. Selection and determination of model parameters

According to the above *DBL* and *CRK*, *DBL* and *SF* respectively regression model and various forms of model try to comparison analysis, that *DBL* as dependent variable and *CRK*, *SF* as an independent variable closer to the linear relationship. For further verification, *CRK* and *SF* data accumulated 168 months were imported into the SPSS software. Multiple linear regression and multivariate nonlinear regression were performed respectively. The constant items and Variable coefficients are seen in Tables 4 and 5.

Table 4. SPSS multiple linear regression coefficient.

model	Non-standardized coefficient		Standard factor	t Sig.	
	B	Standard error	trial version		
(constant)	0.181	0.013	—	14.099	0.000
CRK/Month	5.701	0.663	1.523	8.601	0.000
SF/Month	0.309	0.094	0.585	3.300	0.001

Table 5. SPSS non-linear regression parameter estimates.

parameter	Estimate Standard error		95% Confidence interval	
			Lower limit	Capped
a	-0.336	0.028	-0.390	-0.281
b	4.949	0.218	4.520	5.379
c	0.077	0.011	0.055	0.099

As can be seen from Table 4, the coefficients of *CRK* and *SF* in regression equation are 5.701 and 0.309. When the two indexes of *CRK* and *SF* tend to 0, the constant term is 0.181. The initial *DBL* in multivariate linear regression is also relatively small, and the evaluation result is reasonable. In table 5, the confidence intervals of the three parameters of the nonlinear equation do not contain 0, which proves that all three parameters are statistically significant. However, when the *CRK* and *SF* tend to be 0, *DBL* is negative. As an index to evaluate the damage status of concrete pavement, *DBL* can not have a negative value, which is inconsistent with the actual project situation and inconsistent with the positive correlation in the above correlation analysis. In addition, though the SPSS software for multiple linear regression, use the stepwise regression method, the correlation coefficient R^2 from 0.892 to 0.899. In summary, the prediction model for the damage of *concrete* pavement in seasonally frozen regions is:

$$DBL = 0.181 + 5.701CRK + 0.309SF \tag{4}$$

In order to validate the effectiveness of the predictive model for predicting the damage of concrete pavement in seasonally frozen regions, SPSS software was used for statistical analysis. CRK and SF were all considered as independent variables, and global analysis was conducted by stepwise regression. The order of entry was CRK, SF, and no variables were removed, the results of stepwise regression analysis in Table 6. From the analysis of the model, all the variables and constant items passed the parameter test, and all are positive, which is consistent with the actual situation. From the Table 6, the contribution rate of variance is more than 90 % from itself, Eigen values are only 2.887 and less than 10 (SPSS parameters are considered to be collinearity when the default number of states is greater than 10); the maximum value of conditional index is 24.03 and less than 30 (SPSS parameters are considered to be collinearity when the default number of states is greater than 30) There is no multicollinearity. The above analysis validates the stability of the prediction model for the damage of concrete pavement in seasonally frozen regions.

Table 6. Collinearity diagnosis.

model	dimension	Eigen values	Conditional index	Variance ratio		
				constant	CRK/Month	SF/Month
1	1	1.932	1.000	0.030	0.030	—
	2	0.068	5.324	0.970	0.970	—
2	1	2.887	1.000	0.010	0.000	0.000
	2	0.111	5.090	0.330	0.000	0.010
	3	0.001	24.030	0.660	1.000	0.990

In order to verify the accuracy of the predictive model for predicting the damage of concrete pavement in seasonally frozen regions, the prediction data of the prediction model of concrete pavement damage in seasonally frozen regions are derived from the measured data of Mudanjiang to provincial boundary in He-da highway as shown in Figure 8: The predicted value of the transitional model in the region from 2012 to 2016 is closer to the measured value of DBL than the predicted value of the traditional model of Sun Lijun, which shows that the accuracy of the prediction model is guaranteed.

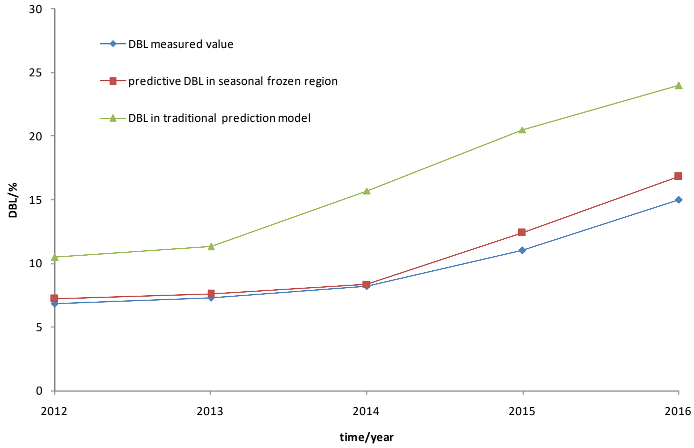

Figure 8. DBL predicted and measured values contrast.

4. Conclusion

1. DBL showed obvious differences with different traffic load and environmental factors. When the road age and climate status of the survey section are consistent, the difference in traffic volume accounts for 3.45 % ~ 6.23 % of the total traffic volume in the survey interval. The difference in the width of the pavement crack is between 8.067 and 55.681 m. When the quantity and the road structure are consistent,

the annual average temperature is 6.1 °C and 14.5 °C, respectively, and the width of the road surface crack caused by the climate difference is between 64.795 and 248.937 m.

2. There was a large difference in SF between seasonally frozen and non-seasonally frozen regions. When the annual average temperature between the seasonally and non-seasonally frozen areas differs by 8.4 ~ 10.2 °C, the SF of the surveyed section of the seasonally frozen area is 10.6 ~ 17.84 times larger than that of the non-seasonally frozen area.

3. Indicator CRK and SF have a strong positive correlation with DBL, which ensures the correctness of the linear correlation of the model. The correlation coefficient between DBL and CRK is 0.944, while the correlation coefficient between DBL and SF is 0.924, with significance level being 0, less than 0.05, and the correlation between CRK and SF and DBL is positive and strong.

4. The predictive model for the damage of concrete pavement in seasonally frozen regions can predict the damage condition of the concrete pavement through the parameters of traffic load, road age, freezing index and so on. In the collinearity diagnosis of the model, more than 90 % of the variance comes from itself. The maximum eigenvalue is only 2.887, less than 10. The maximum value of the conditional index is 24.03, which is less than 30, which proves that there is no multicollinearity problem at this time.

5. The predicted value of the model is closer to the measured value of DBL than the predicted value of traditional model, which ensures the accuracy of the model prediction.

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