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**Panel Data Analysis of Surface Skid Resistance for Various
Pavement Preventive Maintenance Treatments Using Long
Term Pavement Performance (LTPP) Data**

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**PANEL DATA ANALYSIS OF SURFACE SKID RESISTANCE FOR VARIOUS
PAVEMENT PREVENTIVE MAINTENANCE TREATMENTS USING LONG
TERM PAVEMENT PERFORMANCE (LTPP) DATA**

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ABSTRACT

Various preventive maintenance (PM) treatments have been employed to restore pavement skid resistance for enhanced safety. This paper investigates the effectiveness of PM treatments using Panel Data Analysis (PDA). PDA investigates the differences of cross-sectional information among treatments, but also the time-series changes within each treatment over time. Panel data with multiple years of friction data for four treatments (thin overlay, slurry seal, crack seal, and chip seal) at various climate, traffic and pavement conditions are obtained from 255 Long Term Pavement Performance (LTPP) testing sections. Both fixed- and random-effects models are developed to evaluate pavement skid resistance performance and to identify the most influencing factors. Results from the PDA models are compared to those from traditional ordinary regression models. Slurry seal is demonstrated to be the most effective treatment. Five factors (precipitation, freezing index, and humidity, traffic, pavement age) are identified to be significant for pavement friction. Fixed-effects panel model is selected for the development of friction prediction models. This study not only demonstrates the capability of PDA for analyzing friction data with cross-sectional and time-series characteristics, but also can assist engineers in selecting the most effective PM treatments for desired level of skid resistance to reduce traffic crashes.

Keywords: Pavement Skid Resistance, Preventive Maintenance, Panel Data Analysis, Fixed-Effects Model, Random-Effects Model

INTRODUCTION

An effective transportation system should facilitate safe and efficient driving environments for vehicles. Sufficient friction (skid resistance) between tire and pavement plays a crucial role to reduce traffic accidents. However, pavement friction performance deteriorates with time under various factors such as climate conditions and traffic loading. Therefore, continuously monitoring of pavement friction and understanding the long-term friction degradation is of great significance for the development of effective pavement maintenance practices to improve pavement friction performance over total service life (Wang 2013).

Preventive maintenance treatments have been employed by many highway agencies to restore pavement friction and retard future deterioration. The effectiveness of different pavement preservation treatments have been studied in the past decades. Prapaitrakul et al. (2005) investigated the effectiveness of fog seal, while Li et al. (2012) evaluated the long-term friction performance for chip seal, fog-chip, rejuvenating seal, microsurfacing, ultrathin bonded wearing course (UBWC), and thin overlay. Wang (2013) used boxplot and Fisher's Least Significance Difference test to rank the effectiveness of preservation treatments on friction. Li et al. (2016) studied the effectiveness of high friction surface treatment (HFST) in improving pavement friction.

Many research efforts have been conducted to evaluate the most influential factors on surface friction. Cenek (2004) investigated the sensitivity of skid resistance of chip seal surfaces to aggregate and texture characteristics under different traffic loading. Asi (2007) evaluated the pavement friction performance of different asphalt concrete

mixes, including mix with 30% slag, Superpave, Stone mastic asphalt (SMA), and Marshall Mixes. Using friction data of eight different surface textures obtained from 197 Long Term Pavement Performance (LTPP) sections, Ahammed & Tighe (2008) found that tined or grooved surfaces maintained consistently higher friction over time, and that aggregate quality is the predominant factor for asphalt pavement surface friction. In order to investigate the relationship between the shape characteristics of aggregate and the pavement surface properties, Sengoz et al. (2014) found basalt type aggregates display higher friction values compared to limestone aggregates. Based on long-term monitoring of friction coefficients on different asphalt pavement surfaces, Kotek & Florkova (2014) found direct characteristics includes age of wearing course, traffic volume, and climate of section, other factors such as speed, temperature, tire pressure, type of road surface could affect pavement friction. Li et al. (2016) found average temperature and installation age significantly affect the skid resistance based on extensive data collection on HFST sites.

In addition, various friction prediction models have been developed and evaluated in the past decades. Burchett (1978) utilized traditional regression analysis to evaluate the seasonal variations of pavement skid resistance. Fuentes et al. (2010) investigated the effect of pavement roughness on skid resistance using regression analysis and analysis of variance (ANOVA). Rezaei et al. (2011) developed traditional statistical skid resistance prediction models based on measurable quantities such as aggregate characteristics, aggregate gradation, and traffic. Kane et al. (2014) utilized 'Hilbert–Huang transform' (HHT) to develop texture parameters from pavement profiles and thus to investigate the

pavement friction–texture relationship. Kanafi (2014) studied the macro- and micro-texture variations on pavement friction and developed prediction models.

Despite extensive studies, knowledge gaps still remain in understanding the variations of pavement surface skid resistance subject to different preservation treatments. Most existing models have primarily been estimated using cross-sectional (considering multiple individual pavement sites) or time-series (considering multiple observations on one site) friction data. However, for long term performance monitoring, pavement performance data including friction are generally observed multiple times at a specific interval for many pavement sections. These data, which combine cross-sectional and time-series characteristics, are called panel data which allow researchers to construct and test realistic behavioral models that cannot be identified using only cross-sectional or time-series data (Washington et al. 2011). By blending the cross-sectional information reflected in the differences between subjects, and the time-series or within-subject information reflected in the changes within subjects over time, Panel Data Analysis (PDA) has several advantages, such as the capability to adequately account for the presence of heterogeneity and parameters result in inconsistent or meaningless model, over cross-sectional or time-series data models (Madanat et al. 1997; Hsiao 2007; Washington et al. 2011).

In this paper, PDA is used to investigate the effectiveness of various preservation treatments on pavement skid resistance. The panel data used in this paper are obtained from more than fifty SPS-3 testing sites in the LTPP database, which consists of multiple years of surface friction and relevant data for the four preventive maintenance treatments

(thin overlay, slurry seal, crack seal, and chip seal) under various climate conditions, traffic levels and pavement performance. Panel models, both fixed- and random-effects models, are developed and compared with the traditional ordinary regression models. Pavement friction performance for the preventive maintenance treatments is evaluated and the factors that significantly impact pavement skid resistance are identified.

DATA SOURCES

The friction data used in this study are obtained from the LTPP SPS-3 sites. The LTPP program is a long term study of in-service pavements across the United States and Canada. The SPS-3 experiment was designed to evaluate the effectiveness of different flexible pavement preservation treatments (thin overlay, slurry seal, crack seal, and chip seal) on pavement performance under multiple design factors (climatic zone, traffic loading, initial pavement condition, and structural adequacy etc.) (Hall et al. 2002). There are totally 81 SPS-3 sites with 445 sections, while more than 50 SPS-3 sites have three to seven years of friction data.

Factors influencing pavement friction can be categorized into several groups: highway alignment, environment conditions, traffic characteristics, and driver/vehicle characteristics (Hall and Hanna 2009). In this paper, climate, traffic, pavement surface conditions, and pavement structural adequacy are considered as potential influencing factors for friction model development, as shown in Table 1 primarily due to the data availability in the LTPP database. Many climate aspects affect pavement friction based on the previous study. The climate characteristics used in this study include precipitation, humidity, Freezing Index and temperature. Traffic characteristics include Annual

Average Daily Traffic (AADT), Annual Average Daily Truck Traffic (AADTT) and 18-Kip equivalent single axle load (ESAL). Pavement performance indicators include initial friction, pavement age when PM treatment was applied, pavement cracking, rutting, IRI. Falling Weight Deflectometer (FWD) is the most commonly used device to evaluate pavement structural adequacy. In this paper, the average deflection values at the center and farthest sensors of FWD measurements are used to represent pavement structural adequacy.

The parameters and their data source tables in the LTPP database are as follows:

- Friction: MON_FRICITION
- Annual Average Precipitation (AAP): CLM_VWS_PRECIP_ANNUAL
- Annual Average Temperature (AAT): CLM_VWS_TEMP_ANNUAL
- Annual Average Freezing Index (AAFI): CLM_VWS_TEMP_DAILY
- Annual Average Humidity (AAH): CLM_VWS_HUMIDITY_ANNUAL
- Traffic: TRF_HIST_EST_ESAL
- Treatment Age: SECTION_STRUCTURE_HISTORY
- Pavement Cracking: MON_DIS_AC_CRACK_INDEX
- Pavement Rutting: MON_RUT_DEPTH_POINT
- IRI: MON_HSS_PROFILE_SECTION
- FWD: MON_DEFL_DROP_DATA

PRELIMINARY DATA ANALYSIS

FIG. 1 shows the distribution of friction of SPS-3 pavement sections during the multiple-year period, while Table 2 provides the summary statistics of the selected influencing variables and its correlation to friction value. It is seen that the SPS-3 pavement friction data contains high degrees of freedom and significant variations (or heterogeneity across groups and over time), while the correlations between the influencing factors and friction are generally weak except initial friction. As a result, using ordinary regression modeling method to develop friction models may be subject to omitted variable bias. In addition, the friction data sets contain both cross-sectional characteristics (various maintenance treatments under different climate conditions, traffic levels and pavement conditions) and time-series characteristics (multiple years of observations). Therefore, Panel Data Analysis (PDA) could be an appropriate method for analysis of friction data for various preventive maintenance treatments. PDA allows the control of variables variance which cannot be observed or measured for pavement preventive maintenance treatments across different sites, or variables that change over time but not across entities (such as climate and traffic variables).

PANEL DATA ANALYSIS (PDA)

Panel Models

Panel Data Analysis (PDA), also known as pooled longitudinal or cross-sectional time-series analysis, are composed of a cross section of individual subjects, with many repetitive measurements over time for each individual (Lee and Kim 2005). The main difference distinguishes panel model from cross-sectional regression model is that the

panel model incorporates heterogeneity among subjects, allowing for subject-specific parameters. There are two major types of panel models: fixed-effects and random-effects. In the fixed-effects model, subject specific parameters are treated as fixed parameters to be estimated. Fixed-effects regression is the model to use when it is needed to control for omitted variables that differ between cases but are constant over time. However, in the random-effects model, these parameters are treated as random variables from an unknown population (Croissant and Millo 2008). If it is reasonable enough to believe that some omitted variables may be constant over time but vary between cases, and others may be fixed between cases but vary over time, both types of variables can be contained by using random-effects models. Both fixed- and random-effects models are studied and compared in this research.

The equation of panel models is shown in the following:

$$y_{itj} = \alpha_i + x_{itj,1}\beta_1 + x_{itj,2}\beta_2 + x_{itj,3}\beta_3 + x_{itj,4}\beta_4 + \varepsilon_{itj} \quad (1)$$

Where y_{itj} = pavement friction for the i th preventive treatments, t th time period, j th sites; i = subject, preventive treatments ($i = 1, 2, \dots, 5$); t = time, year; j = each site, ($j = 0, \dots, N_{it}$); N_{it} = number of total sites for the i th preventive treatments, t th time period; $x_{itj,1}$ = climate variables; $x_{itj,2}$ = traffic variables; $x_{itj,3}$ = pavement condition variables; $x_{itj,4}$ = structural adequacy variables; ε_{itj} = error term for the i th preventive treatments, t th time period, j th sites;

In the fixed-effects model, subject specific variable, α_i is supposed to be fixed and known parameters, and ε_{itj} is assumed to vary non-stochastically over i or t making the fixed-effects model analogous to a dummy variable model in one dimension. On the

contrary, in the random-effects model, α_i is assumed to be a random variable, which is assumed independently and identically distributed with a mean zero and variance σ_ϵ^2 , and ϵ_{it} is assumed to vary stochastically over i or t requiring special treatment of the error variance matrix (Hsiao 1999).

Model Selection Criteria

Several types of alternative models can be used for the model development, including the Ordinary Least Square (OLS) model, fixed-effects panel model, and random-effects panel model. The process of selecting an appropriate model type is illustrated in FIG. 2. F-test is performed to test the joint significance of the fixed-effects intercepts to compare the regular OLS model and fixed-effects model (Washington et al. 2011). The null hypothesis is that all of the fixed effect intercepts are zeros. If the null hypothesis is rejected, fixed-effects method is preferred and should be used.

The random effects of panel data models can be examined using the Lagrange multiplier (LM) test (Breusch and Pagan 1980; Washington et al. 2011). LM test examines if individual (or time) specific variance components equal to zeros. If the null hypothesis is rejected, significant random effects are presented in the panel data, indicating that the random-effects model can better deal with heterogeneity in the panel data than the OLS model.

In addition, Hausman test (Greene 2012) is conducted to differentiate the fixed and random effects within the panel models. This test evaluates the consistency of an estimator when compared to an alternative, less efficient estimator which is already known to be consistent. Consider the linear model $y = bx + e$, where y is the dependent

variable and x is vector of repressors, b is a vector of coefficients and e is the error term. There are two estimators for b : b_0 and b_1 . Under the null hypothesis, both of these estimators are consistent, but b_1 is efficient with the smallest asymptotic variance. If null hypothesis is rejected, it means that b_1 is inconsistent. In other words, random-effects model is preferred under the null hypothesis due to its higher efficiency, while under the alternative hypothesis fixed-effects model is at least consistent and thus preferred.

Analysis Results and Model Development

The statistical analysis in this research is based on the programming language of R. Traditional OLS regression model, which does not consider the heterogeneity across groups or time, is firstly used to model the friction data. Parameter estimates and the corresponding t-statistics for the OLS models are shown in Table 3. Subsequently, parameter estimates and the corresponding t-statistics for the fixed-effects and random effects models are shown in Table 4 and Table 5 respectively.

To select an appropriate model type for friction prediction model development, F-test, LM test, and Hausman test are performed and the results are shown in Table 6. Since p-value of F-Test is approximately 0, which is much smaller than 0.05, the null hypothesis is rejected at 95% confidence level, indicating that not all of the fixed effect intercepts are zeros. As a result, fixed effect panel model should be preferred as compared to the OLS model. For the LM test, the p-value is approximately 0, and thus the null hypothesis is rejected, indicating that there are significant random effects in the panel data, and thus random effects model is preferred over the OLS model to handle

heterogeneity within the panel data. Finally, in favor of selecting the fixed-effects rather than the random-effects model is the Hausman test presented in Table 6. The p-value of Hausman Test is 0.0006 and the null hypothesis is rejected at 95% confidence level, indicating that random-effects model is inconsistent and fixed-effects model should be selected as the best fit for the final model development.

Compared with cross-sectional or time-series data, panel data raise new specification issues that need to be considered during analysis. The most important of these is cross-sectional bias, which should be the central focus of panel data analysis (Washington et al. 2011; Greene 2012). Statistically, fixed-effects model always provides consistent results but may not be the most efficient solution. On the other hand, random-effects model is generally more efficient (such as better P-values and higher adjusted R-squared value), but may not be consistent. The Hausman Specification Test is one of the most widely used methodologies to determine whether endogeneity bias exists in this model, and select whether the fixed or random effects model should be used. The research question is whether there is significant correlation between the unobserved unit-specific random effects and the regressors. If there is no such correlation, then the random-effects model may be more powerful and parsimonious. If there is such a correlation, the random-effects model would be inconsistently estimated and the fixed-effects model would be the model of choice. In this paper, based on Hausman test results, the random-effects model is inconsistent, and thus the fixed-effects model is selected, which is consistent but not as efficient comparing to the random-effects model. As a result, even though the R-squared value for the random model is higher, fixed-effects

model is used due to its consistency which is more important for panel data models. In addition, R-squared value is generally a suitable measure for prediction, while the major purpose herein is to identify the significant effect of dependent variables.

Fixed-effects panel regression models involve subtracting group means from the regressors. In other words, only time-varying regressors are included in the model. Since IF does not vary with time, the subtraction of the group mean from this variable will result in zero values, and therefore it is excluded from fixed-effects model. As shown in Table 4, for fixed-effects model, the significant effect factors include: climate conditions (precipitation, freezing index, and humidity), traffic (AADTT), pavement age, and area of fatigue cracking. As abovementioned, the fixed-effects model is selected based on the Hausman test. Fixed-effects models are designed to study the causes of changes within an entity, while OLS to study the causes of the entirety without time series effects considered. In this paper, both cross-sectional and time-series attributes of the data sets from various PM treatments are considered in the fixed-effects model, the significant variables of fixed-effects model may not be in line with the OLS method.

The impact of one unit change of the significant influencing factors on friction measurement is provided in Table 7 and the trend charts of friction to the most significant variables are shown in FIG. 3 using least square dummy variable model (LSDV), which is the most widely used approach to revealing fixed-effects of the variables. It is observed that the friction is not highly sensitive to the five variables. Other factors, such as the aggregate properties which may have significant impacts on surface friction, are not considered in this paper due to the availability of the data sets in the LTPP database.

However, these five charts could clearly demonstrate the trend and relative sensitivity of each variable used in the study, which may help highway agencies better selecting preventive maintenance to improve skid resistance performance. In addition, despite of the data limitations, one important purpose of this paper is to prove the feasibility and capability of PDA methodology for analyzing pavement surface friction data with cross-sectional and time-series characteristics. Meanwhile, the analysis results from this study generally agrees with those from previous studies (Kokkalis and Panagouli 1998; Jayawickrama and Thomas 1998).

Even though different factors impact friction at various levels, the intercepts for each individual variable for the four preventive treatments shows consistent ranking with high to low sequence: slurry seal > thin overlay > chip seal > cracking seal > control section. Therefore, all the four preservation treatments result in improvements of pavement skid resistance as compared to the control section without any treatment. Slurry seal is the most effective treatment, followed by thin overlay and chip seal. Cracking seal outperforms control section on skid resistance, but the friction improvement is minor. The scatterplot shown in FIG. 4 also supports this observation for the four treatment types, which is also consistent to the results from several previous studies (Hicks et al. 1997; Song et al. 2005)

Subsequently, fixed effects panel model considering only the five most significant influencing factors is developed and the results are shown in Table 8. All the five factors remain to be significant for the prediction of friction. The R-squared values of the fixed-effects model is 0.94, indicating that the model explains most of the variability of the

response data around its mean and the model fits the data well.

CONCLUSIONS

Panel data analysis are conducted in this paper to identify the most influencing factors of friction for four preventive maintenance treatments using data from the LTPP SPS-3 pavement sites. A dozen of factors from three categories: characteristics of traffic, climate and pavement performance, are examined to evaluate their impacts on pavement friction. The fixed-effects panel model is determined to provide the best estimates for friction with the following findings from this study:

- Slurry seal is the most effective friction improvement among the four preservation treatments under study. Thin overlay and chip seal shows improvements of friction, while cracking seal doesn't cause apparent friction improvement as compared to performance of the control section.
- Several climate characteristics, including precipitation, freezing index, and humidity, have been determined to significantly affect pavement friction. However, temperature is not a key factor affecting pavement surface friction based on the data used in the study.
- Traffic volume in terms of AADTT shows strong correlation with pavement friction, while AADT does not present significant impact on friction possibly due to the incompleteness of AADT data.
- Pavement age and area of fatigue cracking are among the most influential factors on pavement friction. However pavement roughness (IRI) doesn't show consistent correlation with friction.

- Statistics of OLS model, fixed-effects and random-effects panel models are developed and compared. Fixed-effects panel model is identified to be the most suitable model and the regression prediction model is developed to assist engineers in selecting the most effective preventive maintenance treatments. Precipitation and freezing index show positive correlations with friction, while humidity, AADTT and pavement age show negative correlations.

It should be recognized that the data used in the study are obtained from the LTPP database, which are extensive but many important factors such as aggregate properties are not directly considered due to the unavailability of the data.

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Draft

LIST OF TABLES

Table 1. Candidate Variables for PDA

Table 2. Description of Indicator Variables

Table 3. Coefficient Estimates and t-Statistics for OLS Model

Table 4. Coefficient Estimates and t-Statistics for Fixed-Effects Model

Table 5. Coefficient Estimates and t-Statistics for Random-Effects Model

Table 6. Comparisons of Test Results

Table 7. Sensitivity of Friction to Significant Influencing Factors under Four Treatments

Table 8. Fixed-Effects Model Statistics with the Most Significant Variables

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Table 1. Candidate Variables for PDA

Category	Variable		Description
Dependent variable		Friction	Pavement friction
Independent Variables	Age	Age	Pavement Age
	Treatment Type	Treatment	Subject variable describing preventive treatments, (Categorical data with 1 for thin overlay, 2 for slurry seal, 3 for crack seal, 4 for control section, 5 for chip seal)
	Climate	AAT	Annual Average Temperature (deg C)
		AAP	Annual Average Precipitation (mm)
		AAH	Annual Average Humidity (%)
		AAFI	Annual Average Freeze Index (deg C deg days)
	Traffic	AADT	Annual Average Daily Traffic (AADT)
		AADTT	Annual Average Daily Truck Traffic (AADTT)
		ESAL	18-Kip Equivalent Single Axel Load
	Pavement	IF	Pavement Initial Friction Value
	Condition	LCWP	Length of Longitudinal Cracking within Wheel Path (m)
		LCNWP	Length of Longitudinal Cracking outside of Wheel Path (m)
		Rutting	Pavement Rutting depth (mm)
		Fatigue	Area of Fatigue Cracking (m ²)
		IRI	International Roughness Index (IRI) (m/km)
	Structural Adequacy	ADC	Average FWD Deflection (9-kip) for the Center Sensor(microns)
		ADF	Average FWD Deflection (9-kip) for the Farthest Sensor (microns)

Table 2. Description of Indicator Variables

Variable	Unit	Mean	Median	Std deviation	Minimum	Maximum	Correlation with Friction
Friction	-	43.28	44.50	11.69	12.00	84.50	1.00
AAT	deg C	14.06	14.20	5.60	0.20	23.40	-0.03
AAP	mm	927.60	945.40	392.04	113.80	1965.80	0.03
AAH	%	67.14	69.00	8.32	34.00	84.50	-0.01
AAFI	deg C deg days	275.37	69.00	430.81	0.00	2448.00	-0.05
AADT	-	2363.59	1927.00	1901.45	146.00	11321.00	-0.16
AADTT	-	371.09	249.00	442.93	35.00	3516.00	-0.11
ESAL	KESAL	138.49	74.00	200.89	5.00	2091.00	-0.06
IF	-	45.97	48.00	11.38	19.00	84.50	0.70
Age	Year	16.65	16.00	7.17	3.00	45.00	-0.02
LCWP	m	50.13	4.10	81.67	0.00	410.50	-0.07
LCNWP	m	76.30	0.00	2333.63	0.00	84146.00	-0.04
Rutting	mm	7.92	7.00	4.26	1.00	29.00	-0.08
Fatigue	m ²	19.05	0.00	57.86	0.00	544.40	0.00
IRI	m/km	1.52	1.32	0.66	0.56	4.51	-0.08
ADC	microns	316.53	275.00	173.40	52.00	1084.00	-0.04
ADF	microns	35.19	33.00	12.95	8.00	82.00	-0.05

Table 3. Coefficient Estimates and t-Statistics for OLS Model

Variable	Estimate	Std. Error	t-value	Pr(> t)	Sig. level
(Intercept)	16.011	5.698	2.810	0.005	**
AAP	0.000	0.002	-0.091	0.927	
AAT	0.628	0.155	4.059	0.000	***
AAFI	0.006	0.002	3.302	0.001	**
AAH	0.017	0.088	0.196	0.845	
AADT	0.001	0.000	2.632	0.009	**
AADTT	-0.007	0.002	-3.249	0.001	**
ESAL	0.005	0.003	1.899	0.058	.
IF	0.510	0.034	15.187	0.000	***
Age	-0.044	0.067	-0.653	0.514	
Fatigue	0.022	0.008	2.918	0.004	**
LCWP	-0.007	0.005	-1.474	0.141	
LCNWP	-0.014	0.020	-0.678	0.498	
Rutting	-0.394	0.124	-3.186	0.002	**
IRI	1.703	0.874	1.948	0.052	.
ADC	-0.008	0.003	-2.692	0.007	**
ADF	-0.012	0.034	-0.352	0.725	
R-Squared					0.383
Adj. R-Squared					0.362
P-value					0.000

Significant level=0.1, * Significant level=0.05, ** Significant level=0.01, ***Significant level=0.001

Table 4. Coefficient Estimates and t-Statistics for Fixed-Effects Model

Variable	Estimate	Std. Error	t-value	Pr(> t)	Sig. level
AAP	-0.011	0.003	-3.643	0.000	***
AAT	1.933	1.031	1.875	0.062	.
AAFI	0.011	0.005	2.414	0.017	*
AAH	0.618	0.216	2.862	0.005	**
AADT	0.002	0.001	1.788	0.075	.
AADTT	-0.031	0.009	-3.448	0.001	***
ESAL	0.014	0.021	0.686	0.493	
Age	-0.825	0.338	-2.443	0.015	*
Fatigue	0.025	0.011	2.300	0.022	*
LCWP	0.018	0.009	1.896	0.059	.
LCNWP	-0.007	0.045	-0.162	0.871	
Rutting	0.042	0.315	0.133	0.895	
IRI	-0.878	2.431	-0.361	0.718	
ADC	-0.008	0.009	-0.919	0.359	
ADF	0.059	0.148	0.395	0.693	
R-Squared					0.214
Adj. R-Squared					0.097
P-value					0.000

Significant level=0.1, * Significant level=0.05, ** Significant level=0.01, ***Significant level=0.001

Table 5. Coefficient Estimates and t-Statistics for Random-Effects Model

Variable	Estimate	Std. Error	t-value	Pr(> t)	Sig. level
AAP	-0.003	0.002	-1.377	0.169	
AAT	0.783	0.165	4.732	0.000	***
AAFI	0.007	0.002	3.741	0.000	***
AAH	0.090	0.087	1.029	0.304	
AADT	0.001	0.000	2.185	0.029	*
AADTT	-0.008	0.002	-3.499	0.001	***
ESAL	0.005	0.003	1.814	0.070	.
IF	0.578	0.038	15.100	0.000	***
Age	-0.107	0.077	-1.394	0.164	
Fatigue	0.019	0.007	2.751	0.006	**
LCWP	-0.002	0.005	-0.341	0.733	
LCNWP	-0.010	0.021	-0.452	0.651	
Rutting	-0.344	0.137	-2.510	0.012	*
IRI	1.539	0.888	1.733	0.084	.
ADC	-0.010	0.003	-3.181	0.002	**
ADF	-0.002	0.037	-0.063	0.949	
1 thin overlay	9.105	6.020	1.513	0.131	
2 Slurry seal	13.393	6.143	2.180	0.030	*
3 cracking seal	7.543	6.063	1.244	0.214	
4 control section	8.201	6.231	1.316	0.189	
5 chip seal	8.696	6.064	1.434	0.152	
R-Squared					0.540
Adj. R-Squared					0.516
P-value					0.000

Significant level=0.1, * Significant level=0.05, ** Significant level=0.01, ***Significant level=0.001

Table 6. Comparisons of Test Results

Test	F/H Value	df	P-value	Null hypothesis
F-Test	2.7323	248/220	0.0000	Rejected
LM-Test	173410	1	0.0000	Rejected
Hausman Test	39.391	15	0.0006	Rejected

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Table 7. Sensitivity of Friction to Significant Influencing Factors under Four Treatments

Variable	Coefficient	Intercept				
		Thin overlay	Slurry seal	Cracking seal	Control section	Chip seal
AAP	-0.0003	44.3109	48.7821	41.6692	41.2721	43.4938
AAFI	0.0010	43.7700	48.2500	41.0900	40.7000	42.9000
AAH	-0.0515	47.4923	51.9743	44.8372	44.4903	46.6824
AADTT	-0.004	45.511	50.007	42.701	42.348	44.464
Age	-0.082	45.401	49.851	42.770	42.292	44.562
Fatigue	-0.003	43.898	48.365	41.329	41.153	43.173

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Table 8. Fixed-Effects Model Statistics with the Most Significant Variables

Friction Prediction Model development					
Variable	Estimate	Std. Error	t-value	Pr(> t)	Sig. level
AAP	0.003	0.001	2.260	0.024	*
AAFI	0.002	0.001	2.814	0.005	**
AAH	-0.139	0.056	-2.501	0.013	*
AADTT	-0.003	0.001	-5.123	0.000	***
Age	-0.119	0.042	-2.842	0.005	**
1 thin overlay	53.250	2.970	17.928	0.000	***
2 Slurry seal	57.478	2.973	19.333	0.000	***
3 cracking seal	50.677	2.961	17.115	0.000	***
4 control section	50.178	3.036	16.525	0.000	***
5 chip seal	52.476	2.947	17.809	0.000	***
R-Squared					0.941
Adj. R-Squared					0.940
P-value					0.000

Significant level=0.1, * Significant level=0.05, ** Significant level=0.01, ***Significant level=0.001

LIST OF FIGURES

FIG. 1. Distribution and Heterogeneity of Friction Data

FIG. 2. Panel Data Modeling Process (Park 2011)

FIG. 3. Trend Charts of Friction to Significant Influencing Variables

FIG. 4. Friction Scatterplot Results

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1=thin overlay, 2=slurry seal, 3=cracking seal, 4=control section, 5=chip seal.

FIG 1 JPG

392x444mm (300 x 300 DPI)

Figure 2

348x380mm (300 x 300 DPI)

FIG 3 JPG

173x228mm (300 x 300 DPI)

Figure 4

234x139mm (300 x 300 DPI)