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Accounting for Endogeneity in Maintenance Decisions and Overlay Thickness in a Pavement-Roughness Deterioration Model

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Authors
Gayah, Vikash V
Madanat, Samer

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Accounting for endogeneity in maintenance decisions and overlay thickness in a pavement roughness deterioration model

Vikash V. Gayah, Pennsylvania State University, Department of Civil and Environmental Engineering, 231L Sackett Building, University Park, PA 16802, gayah@engr.psu.edu

Samer Madanat, New York University Abu Dhabi; Department of Civil and Urban Engineering, Tandon School of Engineering, New York University, samer.madanat@nyu.edu

ABSTRACT

Pavement deterioration models are an important part of any pavement management system. Many of these models suffer from endogeneity bias due to the inclusion of independent variables that are correlated with unobserved factors, which are captured by the model's error terms. Examples of such endogenous variables include pavement overlay thickness and maintenance and rehabilitation activities, both of which are not randomly chosen but are in fact decision variables that are selected by pavement engineers based on field conditions. Inclusion of these variables in a pavement deterioration model can result in biased and inconsistent model parameter estimates, leading to incorrect insights. Previous research has shown that continuous endogenous variables, such as pavement overlay thickness, can be corrected using auxiliary models to replace the endogenous variable with an instrumented variable that has lower correlation with the unobserved error term. Discrete endogenous variables, such as the type of maintenance and rehabilitation activities, have been accounted for by modeling the likelihood of each potential outcome and developing individual deterioration models for each of the potential responses. This paper proposes an alternative approach to accommodate discrete endogenous variables—the selectivity correction method—that allows a single model to incorporate the impacts of all discrete choices. This approach is applied to develop a pavement roughness progression model that incorporates both continuous and discrete endogenous variables using field data from Washington State. The result is a roughness progression model with consistent parameter estimates, which have more realistic values than those obtained in previous studies that used the same data.

Keywords: roughness progression model, endogeneity correction, empirical pavement modelling

INTRODUCTION

Rough pavements are undesirable because they adversely affect the ride quality of vehicles on a roadway (Al-Omari and Darter, 1994). Pavement roughness also negatively affects freight vehicles as driving on very rough pavements can cause damage to goods being transported, especially if the goods are delicate. Vehicle operating costs, in terms of fuel consumption and vehicle wear and tear, are strongly influenced by the roughness of the pavement and can be significant. For example, additional operating costs due to rough pavements have been shown to be about one order of magnitude greater than the cost of properly maintaining the roadway surface (GEIPOT, 1982; Paterson, 1987).

In order to properly maintain roadway surfaces, pavement engineers need to have predictions of roadway conditions. For this reason, models of pavement roughness progression have become an important part of infrastructure management systems. These models are used to predict the condition of pavement sections in the future, which can be used to determine when and where to most efficiently allocate funds available for maintenance.

Several pavement roughness models (Ozbay and Laub, 2001; Prozzi and Madanat, 2004; Puccinelli and Jackson, 2007) have been developed using experimental pavement sections subject to accelerated loading patterns. These types of models have limitations, because the deterioration of these sections may not reflect the deterioration process of in-use pavement sections; thus, their applicability is a subject of concern.

Models of pavement roughness deterioration developed using field data, i.e., data from in-use pavement sections, present several problems as well. Some models (Way and Eisenberg, 1980; Kay et al, 1993; Gulen et al, 2001) suffer from misspecification bias because either relevant variables were originally excluded from the model or they were removed from the model due to low statistical significance. The misspecification may limit the models applicability or cause other insignificant variables to appear significant (Paterson, 1987; Prozzi and Madanat, 2003). Other models (Karan et al, 1983; Madanat et al, 2005) suffer from endogeneity bias caused by the inclusion of explanatory variables that are correlated with the model error term. Examples include the inclusion of pavement overlay thickness and maintenance and rehabilitation activities, both of which are design variables selected by pavement engineers based on conditions in the field. Specifically, locations that experience the most deterioration usually have thicker pavement overlays and more frequent maintenance activities performed. The inclusion of these endogenous variables leads to biased and inconsistent estimates of the model parameters. Several methods have been proposed to overcome the endogeneity bias present in models developed using field data. For endogenous variables that are continuous, Madanat et al (1995) demonstrated that instrumental variables could be used to reduce correlation between the endogenous variable (in this case, the presence of pavement cracking) and unobserved error term. For endogenous variables that are discrete, Madanat and Mishalani (1998) proposed a structured econometric approach that combines a discrete choice model to predict the likelihood of each discrete outcome and individual pavement deterioration models for each discrete outcome.

As an alternative approach, this paper proposes the use of the selectivity correction approach to account for endogeneity of discrete independent variables in the development of a pavement roughness deterioration model. This method allows a single model to be developed that describes pavement deterioration for all potential discrete outcomes. This method is combined with the instrumental variable method to simultaneously account for endogeneity in two variables that might be included in a pavement roughness deterioration model: 1) thickness of pavement overlays, and 2) maintenance and rehabilitation (M&R) activities. The resulting model of pavement roughness progression should have more consistent parameter estimates than previous models that do not correct for this endogeneity bias.

The rest of this paper is organized as follows. We first describe the empirical dataset used in this study to develop the model for pavement roughness. Then, we explain the source of endogeneity bias and the methodology that will be used to correct for its presence. Next, we present the results of the model development. Finally, we summarize the conclusions.

DATA

Data for this analysis were obtained from the Washington State Pavement Management System (WSPMS) database. This database consists of pavement condition data collected by the Washington State Department of Transportation along each of its state roads from 1983 to 1999. Roads were divided into unique 0.1-mile long sections and each section was observed multiple times during the duration of the data collection period, resulting in a two-dimensional panel dataset. A total of 352,803 observations were available from 48,484 unique roadway sections. A subset of about 60,000 observations was randomly selected for modeling purposes. This random sampling method was adopted to minimize any potential correlation that likely exists from observations for contiguous or geographically close sections within the dataset. The sample still contains sufficient variability in the explanatory variables, given its large size.

The data included information about the road surface conditions, traffic conditions, environmental conditions, and any maintenance and rehabilitation activities that were performed. A subset of the variables present in the WSPMS database that are relevant to the pavement roughness progression model are:

- Cumulative traffic loading [in equivalent single axel loads, or ESALs]
- Current year traffic loading [ESALs]
- Base thickness [ft]
- Thickness of last overlay [ft]
- Minimum temperature [°F]
- Maximum temperature [°F]
- Annual precipitation [in]
- Time since last overlay [years]
- Time since last maintenance activity [years]
- Type of M&R activity [AC overlay, BST treatment, Maintenance]
- Roughness (IRI) in previous year [cm/km]
- Change in roughness [cm/km]

METHODOLOGY

A linear regression model was used to predict the change in roughness as a function of several of the potential explanatory variables available in the dataset. Because the dataset consists of panel data, a random effects model with two error terms was used (Washington et al, 2003). This type of model includes the random effects of individual roadway sections (invariant of time) as well as a random error term over time at each location. The functional form of this model is presented below in Equation 1.

$$y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_K X_{Kit} + \upsilon_i + \varepsilon_{it} \quad \textbf{(1)}$$

In Equation 1, y_{it} is the change in roughness for section i at time t, $\beta_1, \ldots, \beta_K$ are the model parameters, and $X_{1it}, \ldots, X_{Kit}$ are the explanatory variables. The first error term, υ_i, captures the unobserved heterogeneity (cross sectional variation) between different roadway sections. The second error term, ε_{it}, captures the random error of each section that changes over time. To estimate this model, the two-step generalized least squares (GLS) method was applied (Freedman, 2005). The first step requires the model to be estimated using ordinary least squares regression (OLS) in order to estimate the covariance between error terms. The second step then uses this covariance matrix to calculate more efficient estimates of the model parameters, $\overline{\beta}$, than would otherwise be obtained with traditional OLS.

Similar to an OLS model, the GLS model must still satisfy the Gauss-Markov assumption that the explanatory variables should not be correlated with the error terms in the model for the estimates to be consistent (Rudd, 2000). In modeling pavement roughness, two potential explanatory variables are likely to be endogenous and thus correlated with the error terms: the overlay thickness and the type of maintenance and rehabilitation activity performed. Both of these are design variables that are typically selected by pavement engineers based on the conditions that the pavement section experiences; therefore, they are not randomly chosen and cannot be assumed exogenous (Madanat et al, 1995; Madanat and Mishalani, 1998). This endogeneity needs to be accounted or else estimates of $\overline{\beta}$ will be biased.

Endogeneity in the model was addressed in one of two ways. For the continuous endogenous variable—the thickness of the last overlay—the instrumental variables method was used (Mannering, 1998). In this method, the endogenous variable is replaced in the GLS model by another variable that is: 1) highly correlated with it and 2) uncorrelated with the error terms in the GLS model. Such a variable was obtained by estimating an auxiliary model for the endogenous variable using linear regression. This model was a function of several explanatory variables which may or may not be included in the roughness progression model. The predicted values of the endogenous variable were then substituted for the variable in the GLS model since these predicted values were uncorrelated with the error terms. The use of a continuous instrumental variable changes the roughness progression model to the form presented in Equation 2.

$$y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_{K-1} X_{K-1it} + \beta_K \widehat{X}_{Kit} + \upsilon_i + \varepsilon_{it}, \quad \textbf{(2)}$$

where $\widehat{X}_{Kit}$ is the predicted value of the endogenous variable obtained from the auxiliary model.

For the discrete endogenous variable—the type of M&R action that was performed—the selectivity correction approach was used (Train, 1986; Mannering and Hensher, 1987). In this method, a discrete choice model was developed to estimate the probabilities of selecting one of several M&R options. The probability of selecting M&R alternative *j*, $\widehat{P}_j$, was then used to add a new explanatory variable in the GLS model known as the selectivity correction term. For a logit discrete choice model (which was used here) with *J* different choices, *J-1* selectivity terms could be added to the GLS model. The inclusion of these terms changes the model to the form presented in Equation 3.

$$y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + ... + \beta_{K-2} X_{K-2it} + \sum_{j=1}^{J-1} \gamma_j \lambda_j + \beta_K \widehat{X}_{Kit} + \upsilon_i + \varepsilon_{it} \quad \textbf{(3)}$$

where $\lambda_j = \left\{ \frac{J-1}{J} \log \widehat{P}_j + \sum_{l=1, l \neq j}^{J} \frac{\log \widehat{P}_l}{J} \left[\frac{\widehat{P}_l}{1-\widehat{P}_l} \right] \right\}$ was calculated using the probabilities from the discrete choice logit model and γ_j were parameters to be estimated.

MODEL DEVELOPMENT

This section applies the methodology described in the previous section to develop auxiliary models for endogeneity correction and the final pavement roughness progression model.

Endogeneity correction of overlay thickness

In order to correct for endogeneity in the overlay thickness, we developed an auxiliary model that predicted the overlay thickness as a function of several explanatory variables. The variables were chosen based on our knowledge of pavement design methods. The objective of this exercise was to develop an empirical model that would produce overlay thicknesses that are close in values to those designed by Washington DOT's pavement engineers. The resulting model is presented in Equation 4.

(log of overlay thickness)$_{it}$ = α_0 + α_1*(current traffic loading)*$_{it}$ + α_2*(log of previous roughness)*$_{it}$ + α_3*(time since last maintenance activity)*$_{it}$ + α_4 *(minimum air temp)*$_{it}$ + v_i + e_{it} **(4)**

where v_i and e_{it} are error terms. This model form was developed based on knowledge of factors that affect pavement deterioration and might influence an engineer's decision-making when selecting a new overlay thickness. These factors include traffic conditions (current traffic loading), current pavement conditions (log of prev. roughness), age of the pavement (time since last maint. activity) and environmental conditions (min. air temp).

Table 1 presents the estimates of the parameters α_0--α_4 using the GLS method. The parameter estimates conform to a priori expectations. Thicker overlays are provided for roadway sections that experience heavier traffic volumes (higher value of current traffic loading) and that are in a more deteriorated state (higher value of previous roughness). Thinner overlays are provided for warmer climates since fewer freeze-thaw cycles would be expected. The time since last maintenance activity was found not to be statistically significant. Therefore, while it was expected that thicker overlays would be provided for roadway sections that have not had recent M&R activities performed, this may not be the case.

The model seems to have a very good fit, as evidenced by the high R-squared value (0.882). Additionally, the random-effects model is appropriate, due to the high heterogeneity across pavement sections. σ_v^2 represents the variance of the random disturbance v_i, shown in Equation 4, capturing the unobserved heterogeneity between different roadway sections in the panel data. σ_e^2 represents the variance of the random disturbances e_{it} in Equation 4 and accounts for random errors that occur across time and roadway sections. The ratio of the variance of the error terms between different roadway sections to the total variance ($\sigma_v^2 + \sigma_e^2$) shows that unobserved heterogeneity represents a high fraction of the total unobserved variation in the model (0.856).

Endogeneity correction for M&R activity type

In order to correct for endogeneity bias in M&R activity decisions, we developed a model that predicted the probabilities of performing various M&R activities using a multinomial logit (MNL) model. The objective was to represent empirically the process by which Washington DOT engineers select the M&R treatments to apply to different pavement sections. Four possible activities were available: do-nothing, AC overlay, BST treatment, and routine maintenance. The probability of selecting activity *j* is given by Equation 5.

$$\Pr(i) = \frac{\exp(V_j)}{\sum_{j=1}^{J} \exp(V_j)} \quad \textbf{(5)}$$

where V_j is the utility of alternative *j*. The utilities of the various M&R activities were modeled as a function of several explanatory variables, chosen based on assumptions about M&R decision-making. The resulting model specification is presented in Equation 6.

utility of AC overlay = $\theta_0 + \theta_1$*(log of previous roughness)* + θ_2*(overlay age)* + θ_3*(current year traffic loading)*
utility of BST treatment = $\varphi_0 + \varphi_1$*(log of previous roughness)* + φ_2*(overlay age)* + φ_3*(current year traffic loading)*
utility of maintenance = $\psi_0 + \psi_1$*(log of previous roughness)* + ψ_2*(overlay age)* + ψ_3*(current year traffic loading)* **(6)**

Note that these utilities are relative to the do-nothing alternative.

Table 2 presents the estimates of the parameters θ_0--θ_3, φ_0--φ_3, ψ_0--ψ_3 for the MNL model. Most parameter estimates conform to a priori expectations. Compared to the do-nothing alternative, agencies are more likely to perform M&R activities on more deteriorated pavement sections, and more likely to perform AC overlays and BST treatments on the most deteriorated pavement sections as evidenced by the signs and magnitudes of θ_1, φ_1 and ψ_1. Washington DOT pavement engineers are also more likely to perform AC overlay and maintenance activities for pavement sections that experience heavier traffic loading. The model also confirms that agencies are also less likely to apply a BST treatment on pavement sections with higher traffic loading, since BST treatments are usually selected for lower-traffic segments by Washington DOT engineers (Li et al, 2008).

A higher value of overlay age was found to increase the probability of performing an AC overlay but *decrease* the probability of performing routine maintenance (as compared to doing nothing). While this may initially seem counter-intuitive, it actually makes perfect sense from an agency perspective. As an overlay ages, decision makers may put off routine maintenance for that roadway section because they know a new overlay will be applied in the near future. Therefore, as overlays ages, the probability of doing nothing or performing an AC overlay will increase, but the probability of performing routine maintenance will decrease. Note that overlay age was found to be statistically insignificant for the BST treatment activity.

The MNL model has a goodness-of-fit value (ρ^2) of 0.061. While this is not high, it should be remembered that goodness-of-fit values for discrete models are always much smaller than those of regression models, and most variables are statistically significant. Additionally, a log-likelihood test was performed and this had a p-value of 0.00 which means that the model is indeed statistically significant. Therefore, this model was used to determine probabilities of performing different M&R activities in the endogeneity correction. Using the different probabilities, the correction terms for M&R activities were calculated as shown in Equation 3.

Model for pavement roughness progression

Using the results of the previous two models correcting for endogeneity, we developed the model of interest, which predicts pavement roughness progression (the increase in roughness between two observations) as a function of several explanatory variables. The explanatory variables were chosen based on knowledge of pavement deterioration and included environmental variables, pavement variables, traffic variables, and the endogeneity corrections. Note that for the M&R correction, we only included the correction term for the AC overlay because BST treatments and routine maintenance are not performed to directly correct for pavement roughness. The model is presented in Equation 7.

$$\begin{aligned}&(\textit{change in pavement roughness})_{it} = \beta_0 + \beta_1(\textit{previous pavement roughness})_{it} + \beta_2(\textit{cumulative traffic loading})_{it} + \beta_3(\textit{predicted overlay thickness})_{it} + \beta_4(\textit{base thickness})_{it} \\ &+ \beta_5(\textit{min. air temp})_{it} + \beta_6(\textit{precipitation in current year})_{it} + \beta_7(\textit{overlay age})_{it} + \beta_8(\textit{AC overlay correction term})_{it} + \upsilon_i + \varepsilon_{it}\end{aligned} \quad \textbf{(7)}$$

where υ_i and ε_{it} are error terms.

Table 3 presents the estimates of the parameters β_0--β_8 using a random effects model and estimated using the GLS method. Overall, the model seems to have a good fit, as evidenced by the moderately high R-squared value (0.413). Further, it is clear that unobserved heterogeneity is present and thus the use of GLS is appropriate, given the value of the error ratio (0.164).

The estimates of the coefficients conform to a priori expectations. The model predicts that, all else constant, pavement roughness progression is concave—the change in roughness decreases as pavements become rougher. This concave deterioration pattern has also been observed in the WSPMS data for cracking (Madanat et al, 2010). Pavement roughness progression is also found to increase with cumulative traffic loading, precipitation and overlay age, as expected. Roughness progression decreases for roadway sections with thicker overlays and thicker bases and for higher minimum temperatures.

To determine how changing the probability of performing an AC overlay activity affects pavement roughness progression, we use the results from Table 3 and incorporate the change in λ_j. Figure 1 shows how pavement roughness progression changes as a function of the probability of an AC overlay, assuming the probabilities of performing each of the remaining M&R activities (do-nothing, BST treatment, and routine maintenance) are equal. Note from Figure 1 that pavement roughness progression decreases with the AC overlay probability; i.e., higher probabilities of performing an AC overlay result in lower expected pavement roughness progression, confirming a priori expectations.

Model discussion

Predicted values of pavement roughness deterioration can be estimated using Equation 3 and the parameters in Table 3. To examine how well this model predicts the data used to create the model, cumulative distributions of the predicted and observed values are plotted in Figure 2. Conditional forecasting was applied in which the observed values of the continuous endogenous variable, overlay thickness, were inserted directly into Equation 3. As shown in the figure, the model predicts the data fairly well though there is some over-prediction of large negative values.

In a linear regression model, the parameter coefficients reflect the change in the dependent variable (in this case, the annual change in pavement roughness) due to a unit change in one of the independent variables. However, this model includes endogeneity corrections for maintenance activities that are a nonlinear function of some of the explanatory variables. Therefore, the effect of changing an explanatory variable needs to be examined more closely. Figure 3 shows the effect of changing relevant explanatory variables on the dependant variable both with and without the endogeneity corrections. Variables were examined at their mean value and ±1 and ±3 standard deviations away from the mean. In some cases, this method resulted in a value that was out of the feasible range for the variable; e.g., negative values for variables that must be positive. For such variables (traffic loadings and base thicknesses) either 0 or the minimum observed value was used instead. For the current year traffic loading, a change in this value resulted in a corresponding change in the cumulative loading variable since the cumulative loading variable includes the current year traffic loading. Note that when one variable was changed, all other variables were kept at their mean value in the dataset.

Figure 3 presents the change in roughness when the endogeneity corrections are included and also when the endogeneity corrections are not included, for comparison. The results for some variables (base thickness and precipitation) are exactly the same with and without endogeneity corrections because these variables are not included in the endogeneity correction models.

When endogeneity corrections are ignored we see that the change in roughness increases with traffic loading—the higher the current year loading, the faster the roughness progression. However, when endogeneity corrections are included, the opposite trend occurs. This is because a higher current year traffic loading increases the probability of an AC overlay activity, which reduces the expected change in the roughness as shown in Table 4. The same trend occurs for overlay age; note, however, that the magnitude of the difference is so small that it is not visible in the figure.

For previous roughness, we see that the general trend stays the same both when including and not including the endogeneity corrections, but the magnitude of the change in roughness changes. The magnitude of the expected change is greater when endogeneity corrections are included.

Based on Figure 3, the variables that cause the highest variation in the change in pavement roughness are previous roughness, minimum temperature, precipitation, annual traffic loading and base thickness (in that order). Overlay age does not seem to have much of an effect on the change in pavement roughness as the predicted change in roughness changes very little for the entire range of overlay age.

The coefficient estimates presented in Table 3 can also be compared with those of a previous pavement roughness progression model (Madanat et al, 2005) to see how correcting for endogeneity changes the influence of different variables when M&R activity probabilities are held constant. This comparison shows that by correcting for endogeneity, temperature and precipitation have a more pronounced impact on roughness progression while overlay age has a less pronounced impact. Perhaps more importantly, the previous model had a negative coefficient for cumulative traffic loading, which surprisingly suggests that pavements deteriorate less quickly under heavy loads. After correcting for endogeneity, the sign of this coefficient is now positive which conforms to a priori expectation about the underlying physical process.

CONCLUSIONS

This paper presents a methodology to simultaneously account for endogeneity in pavement roughness models that is created when M&R activities and overlay thickness are included. Pavement overlay thickness is corrected using the instrumental variables method that has previously been shown to improve coefficient estimates (Madanat et al, 1995). The presence of M&R activities was corrected using the selectivity correction method, which to the authors' knowledge has never been used in pavement deterioration models to date. The estimated coefficients in the proposed model all meet a priori expectations and are in accordance with knowledge of pavement deterioration, unlike some of those in the previous model developed with the same dataset (Madanat et al, 2005). The model seems to predict well for values of change in pavement roughness close to the mean and less well for values far from the mean. The inclusion of endogeneity corrections also sheds insight onto the expected change in pavement roughness when M&R decision-making is included. These improved results confirm the importance of appropriate corrections for endogenous explanatory variables, which are common in field data sets, i.e., those consisting of in-service pavement sections.

The model for M&R activities created as a part of the endogeneity correction also revealed that the probability of routine maintenance of a pavement section decreases with age. This makes sense because agencies are more likely to put off performing routine maintenance on a pavement section (which only slows deterioration) if they know a rehabilitation activity will be applied in the near future. Further work is required to confirm that this type of M&R decision-making behavior is also found in the datasets of other highway agencies.

All models were developed using data obtained for in-use pavement sections in Washington State. While these roadways represent a range of traffic and environmental conditions, the model is not likely to be directly transferable to pavement sections in other municipalities. For one, changes in design guidelines, construction procedures and the environment are likely to result in different types of pavement performance. Furthermore, the endogeneity correction methods mimic the decision-making process of pavement engineers in Washington State, which focuses on keeping pavement cracking at very low levels (Madanat et al 2010). It is unlikely that a similar policy is used in some other states or countries. Nevertheless, the overall trends, results and insights are likely to be general and transferable to other locations.

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Table I – Model estimates for overlay thickness

	Parameter Estimate	**T-Statistic**	**P-Value**
Current Year ESALs	4.10E-02	11.05	0.00
Log (Previous Roughness)	6.04E-03	10.83	0.00
Time since last Maintenance	2.46E-05	0.54	0.59
Minimum Temperature	-6.12E-04	-15.37	0.00
Constant	1.37E-01	45.38	0.00
R-squared		0.882	
$\boldsymbol{\sigma_v^2/(\sigma_v^2+\sigma_e^2)}$		0.856	

Table 2 – Model estimates for M&R activity type

	AC Overlay		BST Treatment		Maintenance	
	Parameter Estimate	**P-Value**	**Parameter Estimate**	**P-Value**	**Parameter Estimate**	**P-Value**
Constant	-1.59E+01	0.00	-1.65E+01	0.00	-9.54E+00	0.00
log(Prev Roughness)	2.55E+00	0.00	2.58E+00	0.00	1.76E+00	0.00
Overlay Age	7.42E-04	0.00	---	---	-2.17E-03	0.00
Current Year ESALs	2.62E+00	0.00	-1.18E+01	0.00	1.70E+00	0.00

Table 3 – Model estimates for pavement roughness progression

	Parameter Estimate	**T-Statistic**	**P-Value**
Previous Roughness	-2.43E-01	-43.96	0.00
Cumulative ESALs	2.42E+00	9.88	0.00
Predicted Overlay Thickness	-4.78E+02	-9.38	0.00
Base Thickness	-5.72E+00	-9.73	0.00
Minimum Temperature	-2.68E+00	-19.81	0.00
Precipitation	1.56E-01	16.04	0.00
Overlay Age	1.52E-02	10.16	0.00
AC Overlay Correction Factor	-1.61E+01	-18.23	0.00
Constant	1.42E+02	10.73	0.00
R-squared	0.413		
$\sigma_v^2/(\sigma_v^2+\sigma_\varepsilon^2)$	0.164		

Table 4 – Effect of annual loading on M&R probabilities and roughness progression

		Prob(AC)	Prob(BST)	Prob(M)	Prob(DN)	Predicted Change in Roughness
Current Year Traffic Loading	0	0.04	0.03	0.39	0.54	-10.46
	MEAN	0.06	0.01	0.44	0.50	-13.09
	+1SD	0.07	0.00	0.50	0.43	-15.99
	+3SD	0.11	0.00	0.59	0.30	-20.89