Pavement Pre- and Post-Treatment Performance Models Using LTPP Data

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This paper determines that pavement performance in International Roughness Index (IRI) is affected by exogenous interventions such as pavement age, precipitation level, freeze-thaw level, and lower level preservation maintenance strategies. An exponential function of pavement age was used to represent pavement IRI performance curves. Moreover, this paper demonstrates a method which calculates short-term post-pavement performance models from maintenance effect models and pre-treatment performance models to avoid endogeneity bias but is still integrated with effects of maintenance activities on pavement performance.

INTRODUCTION

Predicting future pavement performance and condition is often the first and most important concern for pavement management plans. In modern pavement management systems (PMSs), pavement forecasting models are the most essential elements affecting many critical management decisions. Indeed, reliable performance prediction models are more important than ever before.

Pavement performance forecasting models are generally used to forecast changes in pavement condition over a future time period. Empirical regression models are the most popular models found in the literature and have greater practical value because of the infinite complexity of the underlying phenomena (AASHTO 1993). The models not only provide the pavement performance future changes in response to the known influential factors that cause the changes in those responses, but also provide the relationship between the performance indicators and influential factors. The model's ability to provide this relationship is important to the study in order to understand how the influential factors affect the performance indicators.

All the previous researchers' studies provide great insight on pavement performance, the influential factors that will affect pavement performance, and the potential problems in model formulation. Drawing from the previous studies, this paper will incorporate the idea of developing pre-treatment performance models and post-treatment performance models separately to avoid endogeneity bias. Additionally, the post-treatment performance models will take into account the effectiveness of different treatments applied at different times and pre-treatment performance models.

Long Term Pavement Performance Program (LTPP) is a comprehensive field-data pavement program. It monitors more than 2,400 pavement test sections across the United States and Canada (Elkins and Schmalzer 2009). LTPP was part of the Strategic Highway Research Program (SHRP) from 1987 to 1992. Now it is managed by the Federal Highway Administration (FHWA) and functions as a partnership with the states and provinces. Pavement performance data were available as International Roughness Index (IRI) in LTPP data. Pavement IRI survey values over years from the LTPP database are used in this study to establish pavement performance models. All qualified LTPP test sections, which include all precipitation, freeze-thaw, and maintenance information, are used in this analysis. So it covers the test sections across United States and some provinces in Canada combining all qualified specific pavement studies (SPS) and general pavement studies (GPS) sections. Only flexible pavement test sections were used in the anlysis. The standard data release (SDR) released in 2010 obtained through LTPP customer support service is the data source used in this research.

LITERATURE REVIEW

Hein and Watt (2005) developed a pavement performance prediction model with age and traffic as explanatory factors. Ozbay and Laub (2001) developed a basic IRI prediction model using initial IRI value (IRI value immediately after a pavement is built and open), pavement age, analysis age, structural number, and cumulative equivalent single axle load (ESAL) during analysis age. Gibby and Kitamura (1992) found that the most influential factors affecting the condition of local pavements are previous pavement condition, time elapsed since last major work, soil classification of roadway drainage, surface thickness, functional classification, and individual jurisdiction. Paterson and Attoh-Okine (1992) summarized that roughness progression in flexible pavement is developed by using traffic loading, strength, age, and environmental factors. Perera and Kohn (2001) summarized that environmental factors significantly affect roughness progression in AC pavement. The aforementioned authors commonly agree on the significance of climatic and age factors' effect on pavement deterioration. Maintenance and rehabilitations are also viewed as important factors that will affect pavement performance. However, some researchers suggest that maintenance and rehabilitations should always be viewed as endogenous variables (Prozzi and Mandanat 2004; Ramaswamy and Ben-akiva 1990). If such variables were incorporated into the model as one of the explanatory variables, then endogeneity bias will occur (Madanat, Bulusu, and Mahmoud 1995). Endogeneity bias is the main reason that some researchers have counterintuitive signs for the parameter estimates of important explanatory variables (Ramaswamy and Ben-akiva 1990).

Researchers such as Lytton (1987) have long recognized the need to develop models that respond to exogenous interventions but are also integrated with effects of maintenance activities. Many researchers tried to perform such tasks by accounting for maintenance and rehabilitation effects and also avoiding endogeneity bias. Maintenance and rehabilitations affect pavement condition directly and often are triggered by the condition of a pavement. In this situation, it is not recommended to include maintenance and rehabilitation directly as exogenous explanatory variables (Ramaswamy and Ben-akiva 1990).

Ramaswamy and Ben-Akiva (1990) developed a model that can simultaneously reflect pavement deterioration processes caused by exogenous influential factors and maintenance activities as a response to deterioration. Pavement condition and maintenance depend both on exogenous factors, as well as on each other. The results show a great improvement on having all the expected signs for all the significant parameters. Therefore, the model appears to be a more realistic one for predicting the deterioration of pavement with effects of maintenance activities. The study was the first to shed light on the difficulties associated with combining deterioration and maintenance. The drawbacks are that 1) the model's fit becomes less precise (R^2 value is 0.28), even though the simultaneous equation estimator gets rid of the endogeneity bias; and 2) the model assumes pavement condition and maintenance simultaneously depend on each other, which makes it difficult to forecast conditions under various maintenance and rehabilitation (M&R) policies. Therefore, the models are less useful to support M&R decision making.

Prozzi and Madanat (2004) developed a pavement performance model by combining experimental and field data. They first developed a ride quality model based on American Association of State Highway and Transportation Officials (AASHTO) road test experimental data and then re-estimated the parameters by applying joint estimation with the incorporation of the field data set. With well-designed experimental data, the endogeneity bias will be avoided. The model shows great benefits of using joint estimation such as improving the forecasts, lowering the estimate variance, and avoiding bias in the parameters. The main drawback of the model is that it requires both field data and well-designed experimental data for the regions with homogeneous weather conditions and level of maintenance activities if such data are not available.

Haider and Dwaikat (2010) introduced the idea of separate analysis pre-treatment performance curves, treatment performance changes, and post-treatment performance curves in simple format. Pre-treatment performance curves are connected with post-treatment performance curves by treatment performance changes. Haider and Dwaikat (2010) analyzed different treatment application timing effects and compared the pavement condition changes to the post-treatment deterioration rates for different timing policies. This method separates pavement performance models from maintenance effect models and finds a way to combine the effect with performance models. The drawback of Haider and Dwaikat's (2010) model is that it requires pre-treatment historical data to formulate pre-treatment performance curves and various post-treatment datasets for different treatment application timings to formulate different post-treatment performance curves. To research the different timing effect for each treatment requires too many post-treatment performance datasets. Such datasets are not always available, and may be too expensive to obtain.

PRE-TREATMENT PAVEMENT PERFORMANCE MODELS

In this paper, two types of pre-treatment performance models are developed. First, a pre-treatment performance model with an absolutely "do nothing" strategy will be developed. Second, the study will develop a pre-treatment performance model with minor preservation level maintenance activities (which only contains routine maintenances such as full depth patching, patching, skin patching, shoulder treatment, and seal coat). The rationale for developing two pre-treatment performance models stems from the fact that minor preservation level maintenance activities may not directly affect pavement surface condition indicators but will lower the deterioration rate with factors such as reducing the amount of moisture infiltrating the pavement structure and protecting the pavement system. To capture the effect of minor preservation level maintenance activities, one can compare performance curves with and without those minor preservation level maintenance activities. Minor preservation-level treatments are often categorized as routine maintenance. The study will assume the same level of minor preservation maintenance as those in LTPP program data.

Inspired by previous researchers' findings and to avoid endogeneity bias, simple regression models are developed using IRI as the dependent variable and pavement age as the independent variable for different precipitation and freeze thaw cycle regions. Traffic factors are not included in the research because of limited range of variation. Ninety percent of the observations used for this study have low traffic volumes. Because traffic factors are not included in the paper, the paper is more for demonstrating the methodology.

Three levels of freeze-thaw regions are defined according to the number of freeze-thaw days within a year. The regions are categorized as no freeze-thaw, medium freeze-thaw, and severe freeze-thaw. A freeze-thaw day is defined by a day's air temperature; if the air temperature changes from less than 0 degrees Celsius to greater than 0 degrees Celsius (or from less than 32 degrees Fahrenheit to greater than 32 degrees Fahrenheit), then that day is counted as one freeze-thaw day (USDOT and FHWA 2010)[1]. Regions are also classified based on levels of precipitation and are defined as a dry region or wet region based on the number of wet days per year. A wet day is defined by a day's amount of precipitation; an amount greater than 0.25 mm (or 0.01 inches), results in the day being counted as one wet day (USDOT and FHWA 2010)[2]. The detailed category information is shown in Table 1.

In Table 1, the values in Size 1 represent the number of observations of segments with do-nothing strategy in the corresponding region; Size 2 values represent the number of observations of segments with performing regular minor preservation activities.

Table 2 summarizes the number of observations for all six analysis regions: no freeze-thaw, dry region; no freeze-thaw, wet region; medium freeze-thaw, dry region; medium freeze-thaw, wet region; severe freeze-thaw, dry region; and severe freeze–thaw, wet region.

Table 1: Definition of Analysis Region for Pre-treatment Performance Models

Freeze-Thaw Region	Definition	Size 1	Size 2
No Freeze-Thaw	0 ≤ freeze thaw days per year < 70	48	697
Medium Freeze-Thaw	70 ≤ freeze thaw days per year < 140	52	955
Severe Freeze-Thaw	140 ≤freeze thaw days per year < 230	21	97
Precipitation Region			
Dry	0 ≤ wet days per year < 100	49	373
Wet	100 ≤ wet days per year < 270	72	1376

Table 2: Analysis Data for Pre-treatment Performance Models

Analysis Region	Size 1	Size 2
No Freeze-Thaw, Dry	15	181
Medium Freeze-Thaw, Dry	22	155
Severe Freeze-Thaw, Dry	12	37
No Freeze-Thaw, Wet	33	516
Medium Freeze-Thaw, Wet	30	800
Severe Freeze-Thaw, Wet	9	60

IRI data in LTPP have shown that IRI over time follows the shape of exponential functional form (Haider and Baladi 2010; Haider and Dwaikat 2010). In this study, the pre-treatment performance curve represented by exponential models as shown in equation (1) was tested, and promising statistical results shown later in the paper support the conclusion that IRI in LTPP can be represented by exponential models.

(1) $IRI_{pre}(t) = \alpha_1 * e^{\beta_1 * t}$

Where

α_1 = model parameters representing the initial value of IRI for pre-treatment performance curve

β_1 = model parameters representing the deterioration rate in IRI for pre-treatment performance curve

t = pavement age in months

Several factors have a role in pavement deterioration. Pavement age in months (t) represents the number of months for a pavement from the initial construction month or most recent reconstruction month. This variable is important because the rate of pavement deterioration is expected to change while pavement is aging. Because of the pavement age's relationship with deterioration, the variable is expected to have a positive sign.

Additionally, moisture is recognized as another important factor in pavement deterioration. The more moisture that penetrates a pavement under the surface layers, the faster the pavement will deteriorate. The freeze-thaw cycle is another important factor in affecting pavement deterioration rate. More frequent freeze-thaw cycles result in faster pavement deterioration.

The initial value of IRI for pre-treatment performance curve, ranged from 0.5 to 1.3 meter per kilometer. In this paper, 0.5 meter per kilometer (m/km) is selected as suggested by Haider and

Baladi (2010). The initial IRI benchmark value of 0.5 m/km was suggested to represent a brand new road condition (Haider and Baladi 2010; Haider and Dwaikat 2010). A typical initial serviceability value (which is considered to be the pavement service index value immediately after the pavement is built and open) of 4.5 pavement service index (PSI) was also suggested by AASHTO (1993). The PSI value of 4.5 roughly equals an IRI value of 0.5 m/km when correlation reported by Al-Omari and Darter (1994) was used: $PSI=5*e^{-0.26*IRI}$. All the above-mentioned literature suggest that when a pavement is brand new the IRI index value can be 0.5 m/km.

PRE-TREATMENT PAVEMENT PERFORMANCE MODEL RESULTS

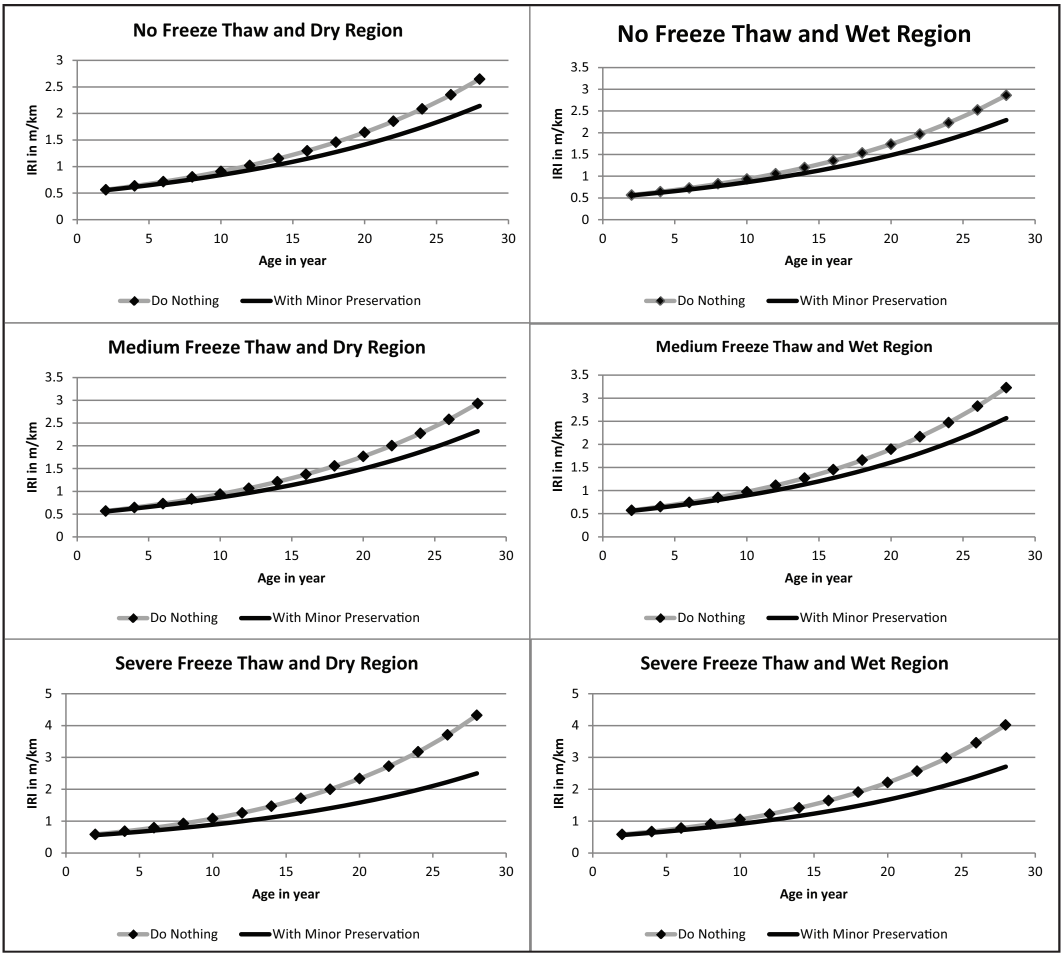
The model's key properties and parameter estimates are shown in Table 3. All 12 models have R-square values higher than 0.69, which suggests that all 12 models explain greater than 69% of the variation in pavement IRI values. The smallest number of observations for the models with minor level maintenance activities is 37, which is sufficient to realize large sample properties. It is rare to truly apply nothing to a pavement, especially to those segments located in a severe weather condition region. So it is not surprising to see that the available data with do-nothing strategy are limited. In this case the least number of observations are found in the severe freeze-thaw, wet region, which only contains nine observations, and the next severe weather condition region is severe freeze-thaw, dry region, which only contains 12 observations. The lowest deterioration rate is found in the no freeze-thaw, dry region with minor preservation activities. It matches expectations since the region is in the least freeze-thaw and the least precipitation affected region. The detailed analyses for each single influential factor will be discussed next.

Table 3: Key Model Properties and Parameter Estimates

Analysis Region	Estimated β_1	Prob. > | t | for β_1	Prob. > F for model	r-square	Adjusted r-square	Observations
With Minor Preservation No Freeze-Thaw, Dry	0.00433	< 0.0001	< 0.0001	0.8502	0.8494	181
With Do Nothing No Freeze-Thaw, Dry	0.00496	< 0.0001	< 0.0001	0.779	0.7632	15
With Minor Preservation Medium Freeze-Thaw, Dry	0.00457	< 0.0001	< 0.0001	0.777	0.7755	155
With Do Nothing Medium Freeze-Thaw, Dry	0.00526	< 0.0001	< 0.0001	0.8103	0.8103	22
With Minor Preservation Severe Freeze-Thaw, Dry	0.00479	< 0.0001	< 0.0001	0.8899	0.8033	37
With Do Nothing Severe Freeze-Thaw, Dry	0.00642	< 0.0001	< 0.0001	0.9143	0.9065	12
With Minor Preservation No Freeze-Thaw, Wet	0.00453	< 0.0001	< 0.0001	0.6913	0.6907	516
With Do Nothing No Freeze-Thaw, Wet	0.00519	< 0.0001	< 0.0001	0.796	0.7315	33
With Minor Preservation Medium Freeze-Thaw, Wet	0.00487	< 0.0001	< 0.0001	0.9055	0.895	800
With Do Nothing Medium Freeze-Thaw, Wet	0.00555	< 0.0001	< 0.0001	0.849	0.8438	30
With Minor Preservation Severe Freeze-Thaw, Wet	0.00503	< 0.0001	< 0.0001	0.8649	0.8626	60
With Do Nothing Severe Freeze-Thaw, Wet	0.0062	< 0.0001	< 0.0001	0.8835	0.8689	9

To compare minor preservation and do-nothing strategies as shown in Figure 1, it is found that the deterioration rate is higher with a do-nothing strategy than with a minor preservation strategy. The result is expected, because it is widely accepted that routine maintenance or minor preservation activities can reduce pavement deterioration rates.

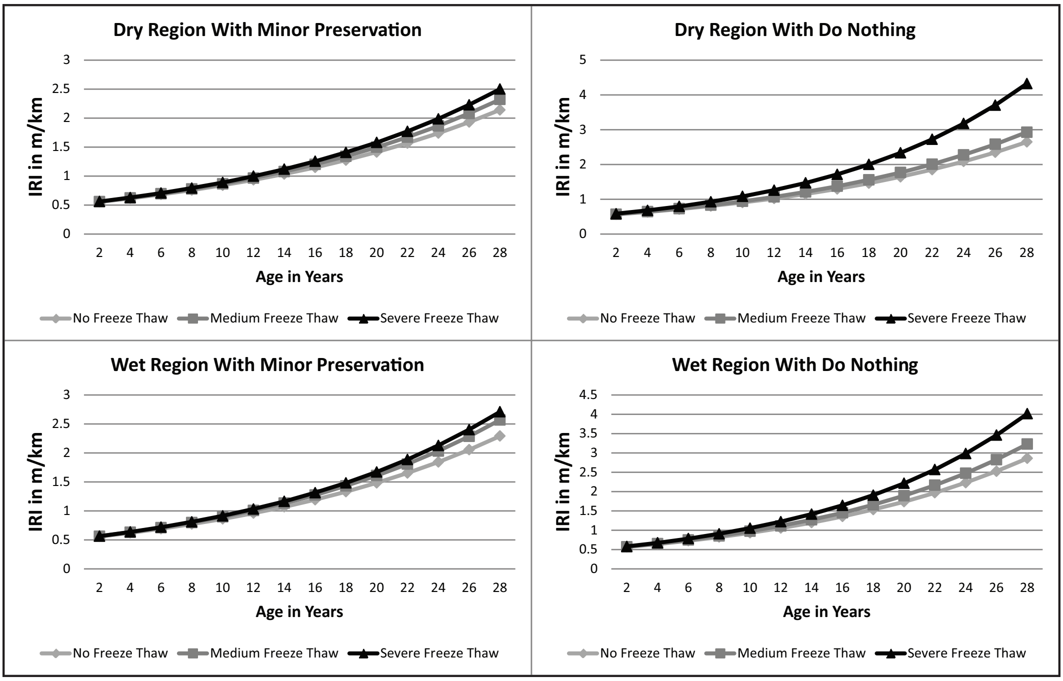
Figure 1: Pre-treatment Performances for Different Minor Preservation Strategies



The deterioration rates for the do-nothing strategy are higher than for the minor preservation strategy, but the magnitudes of the differences for each analysis region are different. Differences in severe weather condition regions tend to be greater than in other regions with less severe weather conditions.

To compare the differences of the freeze-thaw cycle effect shown in Figure 2, it is found that the deterioration rate increases as the freeze-thaw cycle level increases. The result is expected because freeze-thaw activity is commonly thought to accelerate pavement deterioration. The more freeze-thaw cycles within a year, the more quickly the pavement condition will deteriorate.

Figure 2: Pre-treatment Performances for Different Freeze Thaw Regions

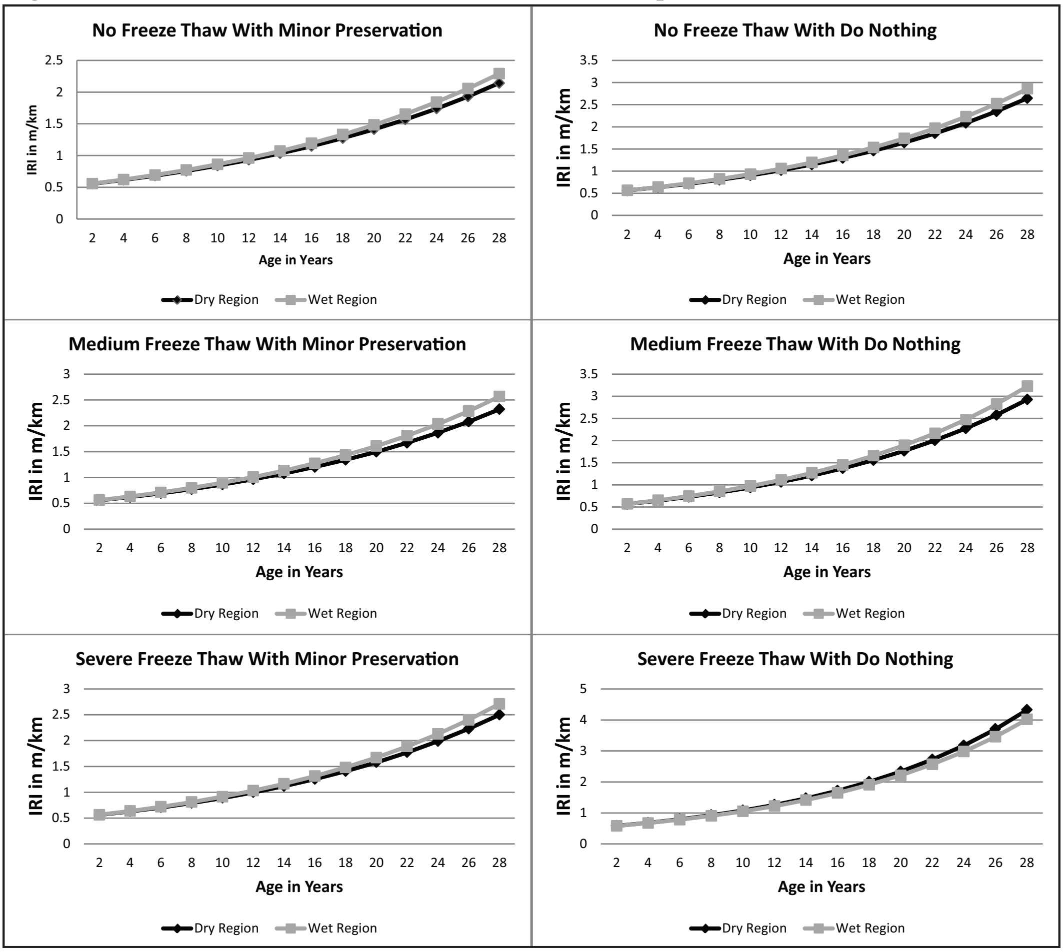


Notice that severe freeze-thaw cycles always have the highest deterioration rates and no freeze-thaw cycles always have the lowest deterioration rates for all four analysis categories. However, the range of differences among three freeze-thaw regions is less for the "minor preservation" strategy than the "do-nothing" strategy. This result shows that minor preservation activities are even more important in severe freeze-thaw regions than in no freeze-thaw regions because such minor preservation activities will decrease the pavement deterioration rate more significantly in severe freeze-thaw regions than in no freeze-thaw regions.

To compare the differences of the precipitation effect, as shown in Figure 3, it is found that, in general, the deterioration rate is higher in wet regions than in dry regions. The result is expected because it is widely accepted that precipitation is an influential factor contributing to pavement deterioration. The more precipitation a region receives within a year, the worse the pavement condition will be or the faster the deterioration rate will be.

The severe freeze-thaw and *wet* region using a do-nothing strategy has a lower pavement deterioration rate than the severe freeze-thaw and *dry* region using a do-nothing strategy. This result is counterintuitive, since the opposite effect is expected: a wet region should have higher deterioration rate than dry region with the same other properties. The reason for the counterintuitive result may be the limited number of observations, nine and 12, respectively. As mentioned before, it is rare to apply absolutely no treatment to a pavement, especially to a pavement located in a severe weather condition region. The result is more like a statistical average than a regression result with an insufficient number of observations.

Figure 3: Pre-treatment Performances for Different Precipitation Levels



POST- TREATMENT PAVEMENT PERFORMANCE MODEL FORMULATION

As mentioned earlier, IRI data in LTPP have shown that IRI over time follows the shape of an exponential functional form (Haider and Baladi 2010; Haider and Dwaikat 2010). Moreover, Irfan, Khurshid, Labi, and Flora (2009) suggested post-treatment pavement performance function has an exponential functional form. In this study, the post-treatment performance curve represented by exponential models as shown in equation (2) was assumed.

(2) $IRI_{post}(t) = \alpha_2 * e^{\beta_2 * t}$

Where

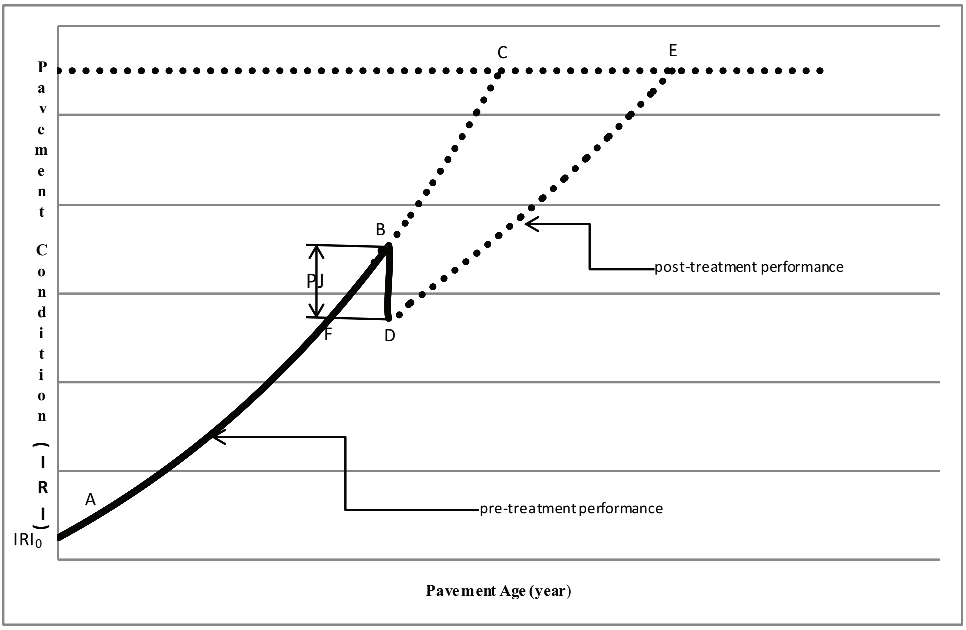
- α_2 = model parameters representing the initial value of IRI for post-treatment performance curve
- β_2 = model parameters representing the deterioration rate in IRI for post-treatment performance curve
- t = pavement age in months since last medium or major preservation activity

Figure 4 shows the relationship between pre-treatment performance curve, short-term treatment performance jump, and post-treatment performance. Figure 4 shows that the pre-treatment IRI follows the pre-treatment performance curve AFBC, unless a treatment is applied at point B, then the IRI value of the pavement will move to point D. The treatment performance jump denoted by PJ is defined as the difference in pavement condition immediately before and immediately after the application of a treatment. Then the post-treatment IRI value will follow the post-treatment performance curve DE.

One can tell from Figure 4 that the post-treatment and pre-treatment performance curves are connected by the treatment performance jump. Then the initial value of a post-treatment curve can be represented by equation (3).

(3) $\alpha_2 = IRI_{pre} - PJ$

Figure 4: Relationship of Pavement Performance and Treatment Performance Jump



With equation (3), pre-treatment performance curve and treatment effectiveness equations, it is not difficult to calculate for a pavement having a treatment applied at any time. Then the next task is to calculate post-treatment deterioration rate. Figure 4 shows the behavior of the post-treatment deterioration rate. A treatment applied to a pavement at point B restores the pavement's surface condition back to the IRI value associated with point D or point F. Treatment should lower the deterioration rate at the moment, which is only the deterioration rate at point D and it is supposed to be no greater than the deterioration rate at point B depending on the effectiveness of the treatment. The treatment should not improve the original condition of the pavement, which is the deterioration rate at point D. It is supposed to be no smaller than the deterioration rate at point F depending on the treatment effectiveness. For example, a reconstruction is considered as the highest effectiveness treatment. If a reconstruction is applied to a pavement, it will restore the IRI value and the deterioration rate back to their original values.

Finding the long-term post-treatment performance deterioration rate, is challenging. If the experimental data after a treatment application at various ages of a pavement are available, it is not difficult to find the post-treatment performance deterioration rate for different treatment application timings. Unfortunately, such data are rarely available and are expensive to obtain. For these reasons, some researchers' studies show unrealistic results.

Haider and Dwaikat (2010) showed that if a treatment is applied early in the pavement's life, it will result a lower treatment performance jump and slower post-deterioration rate. Treatment applied later in the pavement's life results in a higher treatment performance jump and a faster deterioration rate. The conclusion is not always accurate since the higher treatment jump can be combined with slower post-treatment deterioration rate. More specifically, if a treatment has a higher performance jump, it is supposed to lower the deterioration rate at the point instead of increasing the deterioration rate. From Figure 4, the deterioration rate at point D should be no greater than the deterioration rate at point B; and if a treatment has a lower performance jump, it is supposed to lower the deterioration rate at that point, but not lower than the deterioration rate at the after-treatment IRI value point on the pre-treatment curve. From Figure 4, the deterioration rate at point D should be no smaller than the deterioration rate at point F.

The main reason for Haider and Dwaikat (2010) to draw such a conclusion is because of the difficulty to obtain various post-treatment field performance data. They selected one section of pavement post-performance data with one control section of pavement performance data to calculate the treatment effect and deterioration rates. The number of observations is insufficient and the results are very sensitive to the available pavement performance data.

Before the post-treatment performance data become available, one can hardly verify the long-term, post-treatment deterioration rates. However, if researchers only focus on the short term treatment effectiveness, that is researchers only look at treatment performance within one year after a treatment is applied to the pavement, it is realistic to assume that if a treatment can restore the IRI value, it can also restore the deterioration rate based on the new IRI value. As explained in Figure 4, the deterioration rate at point D is the same as the deterioration rate at point F. In this case the pre-treatment deterioration rate, β_1, should be equal to the post-treatment deterioration rate, β_2, because the treatment effect is basically a restoration effect. The mathematical derivation of the relationship is shown in the next paragraph.

If a treatment is applied to a pavement at its age of t_i with a performance jump, PJ_i, the pre-treatment condition can be expressed via Equation (1) as Equation (4) and the pavement age associated with post-treatment IRI condition, t_j, can be expressed via Equation (2) as Equation (5).

(4) $IRI_i^{pre} = \alpha_1 \times e^{\beta_1 \times t_i}$

(5) $t_j = \left[\ln\left(\frac{\alpha_1 \times e^{\beta_1 \times t_i} - PJ_i}{\alpha_1}\right)\right]/\beta_1$

Restored deterioration rate behavior can be expressed as in Equation (6).

(6) $\left.\frac{df_{pre}(\mathrm{t})}{dt}\right|_{t=t_j} = \left.\frac{df_{post}(\mathrm{t})}{dt}\right|_{t=0}$

Where,

f_{pre}(t) and f_{post}(t) are pre-treatment and post-treatment performance functions respectively.
df_{pre}(t) and df_{post}(t) are derivatives of pre-treatment and post-treatment performance functions respectively.

By calculating the derivative of pre-treatment performance curve and post treatment performance functions, one can get Equation (7).

(7) $\alpha_1 * \beta_1 * e^{\beta_1 * t_j} = \alpha_2 * \beta_2$

By substituting Equations (3), (4), and (5) into Equation (7), a relationship between β_1 and β_2 at treatment application time will be obtained as shown in equation (8).

$$(8)\quad (\alpha_1 \times e^{\beta_1 \times t_i} - PJ_i) \times \beta_1 = (\alpha_1 \times e^{\beta_1 \times t_i} - PJ_i) \times \beta_2$$

Since $\alpha_1 \times e^{\beta_1 \times t_i} - PJ_i = \alpha_2$ and α2 ≠ therefore the post-treatment deterioration rate, β_2, equals the pre-treatment deterioration rate, β_1.

In general, post-treatment performance curve function can be expressed in Equation (9).

$$(9)\quad IRI_{jt_i} = (\alpha_1 \times e^{\beta_1 \times t_i} - PJ_{jt_i}) \times e^{\beta_1 \times t}$$

Where

IRI_{jt_i} = post-treatment IRI when treatment j applied to a pavement at t_i

α_1 = model parameter representing the initial value of IRI for pre-treatment performance curve

β_1 = model parameter representing the deterioration rate in IRI for pre-treatment performance curve

t_i = pavement age when a treatment applied to the pavement

PJ_{jt_i} = pavement IRI performance jump when treatment j applied to the pavement at age t_i

t = post-treatment pavement age in months

PAVEMENT PERFORMANCE MODEL VALIDATION

Regression model forecast verification is sometimes called validation, or evaluation. The purpose of this process is to help assess the specific strengths and deficiencies of regression models when they are used to forecast values of the dependent variable using values of the explanatory variables that were not represented in the sample dataset used to estimate the model. Ultimately, this process may provide justifications for uses of the model for forecasting and supporting better decision making (Wilks 2006).

Cook and Kairiukstis (1990) state that reduction of error (RE) "should assume a central role in the verification procedure" (p. 181). RE is an example of forecast skill statistic (Wilks 2006). Wilks (2006) defined forecast skill as the relative accuracy of a set of forecasts with respect to some set of standard controls, which are usually the average values of the predictand. The equation used to calculate RE can be expressed in the following Equation (10).

$$(10)\quad RE = 1 - \frac{SSE_v}{SSE_{ref}}$$

Where SSE_v = sum of squares of validation errors between observed and predicted values over the validation period and SSE_{ref} = sum of squares of validation errors between observed and control values or reference values over the validation period.

Jackknife is a statistical method for systematically computing the statistical estimate leaving out one observation at a time from the sample set (Wilks 2006). One application of the Jackknife procedure is to compare the difference between the omitted observation's value and predicted value for the omitted observation. The difference is defined as validation error. It can be mathematically expressed as Equation (11).

$$(11)\quad e_{(i)} = y_i - \widehat{y_{(i)}}$$

Where y_i and $\widehat{y_{(i)}}$ are the observed and predicted values of the predictand for validation data set i, and the notation (i) indicates that the validation data set i was not used in fitting the model that generated the prediction $\widehat{y_{(i)}}$.

The sum of the squares of errors for validation, SSE_v, can be expressed as Equation (12) and the sum of squares of errors for reference, SSE_{ref}, can be expressed as Equation (13).

(12) $SSE_v = \sum_{i=1}^{n_v} e_{(i)}^2$

(13) $SSE_{ref} = \sum_{i=1}^{n_v} (y_i - \bar{y})^2$

Where n_v is the validation period or the number of validation tests and $\bar{y}$ is the mean of the predictand, which usually serves as a reference or control value.

Using a leave-one-out Jackknife procedure will select one validation data point to exclude from the original dataset at one time, until all the data points are selected once. The regression calculations are repeated n times, which should be the number of observations in the original data set. Notation i in Equation (11) can then be explained as the ith observation in the original dataset, which is selected as the leave-out validation data. Notation n_v in Equation (12) and (13) then should be n. Equation (12) will then be identical to PRESS (the predicted residual sum of squares) and RE can be expressed as Equation (14) and used as the objective model verification statistic in this study.

(14) $RE = 1 - \dfrac{\sum_{i=1}^{n} (y_i - \widehat{y_l})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} = 1 - \dfrac{PRESS}{SSE_{ref}}$

Theoretically, the value of RE can range from negative infinity to one, where one indicates perfect prediction for the validation data set. It will only occur when all the residuals for validation data are zero (i.e. PRESS = 0). On the other hand, if PRESS is much greater than SSE_{ref}, RE can be negative and large. As a rule of thumb, a positive RE indicates that the regression model on average has some forecast capability. Conversely, if RE ≤ 0, the model is deemed to have no ability to predict (Cook and Kairiukstis 1990; Wilks 2006). The similarity in form of the equations for RE and regression R^2 expressed as Equation (15) suggests that RE can also be used as validation evidence for R^2. The closer the values of RE and R^2 are to each other, the more the model is accepted as a predictive tool. RE sometimes is referred as Jackknife R^2.

(15) $R^2 = 1 - \dfrac{SSE}{SST} = 1 - \dfrac{\sum_{i=1}^{n} (y_i - \widehat{y_l})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$

Twelve pre-treatment performance models were developed in this study. The model validation results are shown in Table 4. Difference is calculated by (R-Square – Jackknife R-Square) / R-Square.

Table 4: Forecast Validation of Regression Models

Models	R-Square	Jackknife R-Square	Percent Difference
S-D-Nothing	91.43%	89.87%	1.71%
S-W-Nothing	88.35%	85.17%	3.60%
M-D-Nothing	81.03%	78.37%	3.28%
M-W-Nothing	84.90%	83.94%	1.13%
N-D-Nothing	77.90%	73.03%	6.25%
N-W-Nothing	79.60%	72.05%	9.48%
S-D-Minor	80.87%	79.84%	1.27%
S-W-Minor	86.49%	86.02%	0.54%
M-D-Minor	77.70%	77.26%	0.57%
M-W-Minor	78.63%	78.58%	0.06%
N-D-Minor	85.02%	84.88%	0.16%
N-W-Minor	69.13%	68.98%	0.22%

Table 4 provides several indications about the models: (1) all the models are accepted with consideration of some forecast skills, since all the Jackknife R-Squares are positive values, (2) all the models are accepted as validated models, since most of them have Jackknife R-Square values close to R-Square, and (3) all the models have Jackknife R-Square values higher than 70%. The Jackknife R-Square values shown in Table 4 indicate that most of the models can be accepted as exhibiting higher forecasting ability, since 100% means perfect forecast (Cook and Kairiukstis 1990, Wilks 2006).

SUMMARY AND CONCLUSIONS

This paper presents pre-treatment performance models with exponential form. Moreover, the paper demonstrates a method for determining the post-treatment performance model by using pre-treatment performance models and short-term performance effectiveness.

The pre-treatment models demonstrate several findings. The models reveal that pavement IRI deterioration rate is higher with a do-nothing strategy compared with a minor preservation strategy. However, the magnitudes of the differences for different analysis regions vary. Differences in severe weather condition regions tend to be greater than in less severe weather condition regions. Additionally, deterioration rates increase with a freeze-thaw cycle level increase. However, the range of the differences among three freeze-thaw regions is smaller for a minor preservation strategy region than for a do-nothing strategy region. It shows that minor preservation activities are even more important in severe freeze-thaw regions than in no freeze-thaw regions because such minor preservation activities will lower pavement deterioration rates more significantly in severe freeze-thaw regions than in no freeze-thaw regions. The models also demonstrate that the deterioration rate is higher in wet regions than in dry regions. In most cases, a wet region has higher deterioration rates than a dry region.

The study results can have important implications in the design of pavement preservation strategies decision making. Pavement engineers often need to develop pavement preservation schedules. Knowledge of pre- and post-treatment pavement performance is essential for engineers to decide when and what subsequent preservation activities should be carried out.

Endnotes

1. One might argue that freeze-thawing conditions occur over longer periods than a single day. However, what we defined here is based on FHWA's LTPP's definition, which is based on freeze-thaw days. There is no other way we can obtain the true freeze thaw condition from the available LTPP data.

   We believe the LTPP definition makes sense. Yes, the actual freeze thaw conditions occur over longer periods than a single day. But when the true freeze thaw happens it is always linked to changing temperature from less than 32 to more than 32 degrees. And the definition used here is when freeze-thaw days are less than 70 days in a year, it is considered as no-freeze-thaw category. From 70 freeze-thaw days to 140 freeze-thaw days, it is considered as medium freeze-thaw category. And from 140 to 230 days, it is considered as severe freeze-thaw category. The rationale behind this definition is the more frequent temperature changes from less than 32 to more than 32 in a single day the more likely freeze-thaw condition will happen.

   From the statistical models, the results show a clear difference among the current freeze-thaw level definitions.

2. This is the LTPP definition based on the number of wet days in a year, not the total amount of precipitation within a year. The rationale of the LTPP's definition is the more frequent the wet days within a year the greater the precipitation effect on the pavement.

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