

Research Article

Rutting Model for HMA Overlay Treatment of Composite Pavements

**Mohammad Abdullah Nur, Mohammad Jamal Khattak,
and Mohammad Reza-Ul-Karim Bhuyan**

Civil Engineering Department, University of Louisiana at Lafayette, Lafayette, LA 70504, USA

Correspondence should be addressed to Mohammad Jamal Khattak; khattak@louisiana.edu

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Timely rehabilitation and preservation of pavement systems are imperative to maximize benefits in terms of driver's comfort and safety. However, the effectiveness of any treatment largely depends on the time of treatment and triggers governed by treatment performance models. This paper presents the development of rutting model for overlay treatment of composite pavement in the State of Louisiana. Various factors affecting the rutting of overlay treatment were identified. Regression analysis was conducted, and rut prediction model is generated. In order to better predict the pavement service life, the existing condition of the pavement was also utilized through the model. The developed models provided a good agreement between the measured and predicted rut values. It was found that the predictions were significantly improved, when existing pavement condition was incorporated. The resulting rutting model could be used as a good pavement management tool for timely pavement maintenance and rehabilitation actions to maximize LADOTD benefits and driver's comfort and safety.

1. Introduction and Background

Rutting is considered as one of the major forms of distresses in HMA overlay of composite pavement. Rutting is a surface depression in the wheel paths generally caused by truck tire pressures, axle loads, and traffic volumes [1]. Longitudinal deviation of rut depth in the wheel path is a primary factor in the road roughness which affects serviceability and IRI (International Roughness Index) [2]. Pavement roughness influences pavement ride quality and usually leads to rider discomfort, increased travel times, and higher operational cost for vehicle. In the transverse direction of pavement, rutting along the wheel path hampers drainage characteristics, reduces runoff capability, and causes hydroplaning and loss of friction [3, 4]. Longitudinal crack, which often occurs in deep ruts, induces the penetration of water and other debris, accelerates the rate of deterioration of HMA overlay and underlying PCC layer, and reduces the pavement service life [3].

Regarding HMA overlay rutting, it is commonly believed that rutting is a demonstration of two different mechanisms

and is a combination of densification (change in volume) and repetitive shear deformation (lateral movement or plastic flow with no change in volume) [5]. Both densification and shear deformation are strongly influenced by traffic loading, pavement structure, and pavement material properties. Climate shows significant effect on rutting development, when the subgrade experiences seasonal variations and when the bituminous materials are subjected to high temperatures. Researchers have successfully applied typical pavement distress characteristics, traffic characteristics, and climatic factors to predict rutting over the years. Rutting models based on statistical analysis have been developed by Long Term Pavement Performance (LTPP) program, Mississippi and Washington Department of Transportation (DOT) and other state agencies [6–8]. All such models generally recognize that major factors contributing to the model are load characteristics, site factors, age of pavement, traffic loading, precipitation, temperature, freezing index, cooling index, and thickness of pavement layers [6–8]. All such models are statistically based and the main advantage of which is their simplicity. However, the resulting models are applicable only

TABLE 1: Ranking of overlay treatment based on dominant distress types occurring after application of each of the treatments (a ranking of 1 is the most dominant distress type).

Treatment type	PH	BL	CR	RV	FC	TC	LC	RT	FT	CB
Structural overlay (>2 in)	5.0	8.5	4.7	4.7	3.8	2.3	2.5	2.5	8.5	9.5
Nonstructural overlay (≤ 2 in)	4.0	8.5	4.7	3.7	3.0	2.3	3.0	2.3	8.5	9.5

PH: potholes; BL: bleeding; CR: corrugation; RV: raveling; FC: fatigue cracking; TC: transverse cracking; LC: longitudinal cracking; RT: rutting; FT: faulting; CB: corner break.

within the range of the data used for the development of the model. These models need calibration when used out of their boundary conditions, and often the form of the model has to be modified. Like many other regions, the State of Louisiana, USA, has different weather, traffic, and soil conditions. Some factors like freezing index as used by some existing models are not at all applicable because the state falls under wet-no-freeze zone. Furthermore, Louisiana Department of Transportation and Development (LADOTD) is in the process of developing integrated and comprehensive PMS database that will not only include the pavement distresses but also the climatic and pavement history and inventory data. Such information is commonly used by most models [6]. Timely rehabilitation and preservation of pavement systems are imperative to maximize benefits in terms of driver's comfort and safety and spending of tax payers' dollars. LADOTD's rehabilitation and preventive maintenance of flexible and composite pavements is accomplished using various treatment options including the following: replacement, structural (thick) overlay, nonstructural (thin) overlays, crack sealing, chip seals, micro-surfacing, patching, full-depth concrete repair, and whitetopping.

Overlay has been used to improve ride quality, provide surface drainage and friction, and correct the surface irregularities. Sometimes they have been used without any regard in the cost due to their effectiveness in pavement functional ability [9]. It is a preventive maintenance treatment where HMA is applied to milled or unmilled existing pavement. Louisiana uses overlay treatment of 1.5 inch (3.81 cm) to 7 inch (17.78 cm). Structural overlay (>2 inch (5.08 cm)) is provided to the pavements where the base and subbase soils are weak in strength, and by increasing the thickness the structural capacity of the pavement is improved.

A survey was conducted by the researchers among all the nine districts of the LADOTD for present day practice and detailed information about overlay treatment. Six districts responded to the survey, while three districts did not respond to the survey. The responses from the six districts were analyzed, and it was found that on a yearly basis about 19.45% of the total state lane miles go through some kind of treatment. Among these treated pavement, 15.76% receive structural overlay (>2 inch (5.08 cm)), treatment and 29.59% receive nonstructural overlay (≤ 2 inch (5.08 cm)), treatment. Costs of structural overlay and nonstructural overlay per lane mile are, respectively, \$215,400 and \$157,500 with a treatment life of 10.6 years and 9.8 years, respectively. According to all the districts, ride quality improved significantly after the application of treatments. After treatment, the overlay is affected mainly by rutting and cracking with some raveling,

potholes, and corrugation. The ranking of overlay treatment based on dominant distress type occurring after the overlay application is summarized in Table 1.

From the above information it is clearly seen that a significant amount of pavement receives overlay treatment worth millions of dollar each year in Louisiana. Most of which are susceptible to rutting as it is recognized as one of the most dominant distresses. LADOTD has spent substantial financial resources on various rehabilitation and maintenance treatments to minimize the pavement distresses and improve the pavement life. However, the effectiveness of any treatment largely depends on the time of treatment and trigger governed by treatment performance models. A recent study completed by Louisiana Transportation Research Center (LTRC) regarding the pavement management system (PMS) and performance modeling emphasized the importance of developing treatment performance models [10]. This paper is the result of LTRC-initiated three-phase study that addresses such needs by developing rigorous treatment performance models.

2. Objective

The main objective of this study is to identify various parameters that affect the performance of overlay treatment and to develop rut prediction model for overlay treatment on composite pavements in the State of Louisiana. By developing an applicable model, prediction of treatment life could be made based on actual values obtained from the field. Also, existing condition of the pavement was also incorporated in the model to improve the predictions. To fulfill this purpose, composite pavements subjected to HMA overlay treatment were analyzed. These pavement projects are positioned throughout Louisiana and effectively portray different climatic and soil conditions to establish applicable rutting model for Louisiana.

3. Data Collection and Project Selection

3.1. Pavement Distress Data. LADOTD's mainframe database contains the time-series pavement distress data. The section of the mainframe that contains reconstruction and rehabilitation dates is located in the tracking of projects system (TOPS). The pavement management system (PMS) data has been recorded every two years since 1995 by the automatic road analyzer (ARAN). All such data are reported every 1/10th of a mile based on a location reference system called "control-section log-miles." The department has a numerical coding system for recording cost data and relating it to a segment of

roadway. Each state highway is divided into smaller segments called "Controls," and each Control is divided further into smaller segments called "Section." The state project number usually consists of the control-section of the highway being worked on and a job number on that section. This 1/10th of a mile is also referred to as an element ID in the database.

3.2. Roadway and Project Selection. All roadways where different treatment projects were implemented were identified, with the help of pavement management system (PMS) office, project review committee (PRC), and district engineers. For this purpose, LADOTD database were searched including the PMS database, material testing system (MATT), TOPS, letting of projects (LETS), the Highway Needs, the traffic and planning highway inventory, the maintenance operations system, the traffic volumes data, the pavement design, and system preservation database.

For each pavement project, various tables were generated to include as a minimum information such as data source, project/section identification number (control-section, log-mile, project number, etc.), route name and number (I-10, LA-1, US-90, etc.), roadway classification (National Highway System (NHS) (interstate and others); State Highway System (SHS); and Rural Highway System (RHS)), highway functional classification (arterial, collector, etc.) pavement performance data (distress data, i.e. rut, IRI) before and after treatment, type and cost of the treatment action, type and thickness of the overlay, year/age of construction of treatments, traffic data (ADTT, ESAL, etc.), and all possible maintenance actions (crack repair, grinding and milling, etc.). Highway functional classification is an important parameter in our analysis, and LADOTD classifies the pavement network in to six categories. Name of the classifications and their assigned value based on priority in parentheses are as follows: interstate (1), principal arterial (2), minor arterial (3), major collector (4), minor collector (5), and local road (9).

The tabulated information was then used to select the various pavement sections relative to the available time series treatment performance data (distress data). All pavement sections should have at least one data point just prior to treatment (BT), and three or more data points after treatments (AT) were selected for analysis.

The pavement sections were further scrutinized relative to the available information regarding the treatment type, costs, the pretreatment repairs, and so forth. Considering all the above, 199 pavement projects totaling nearly 931.3 km (578.7 miles) from the State of Louisiana were identified for analysis. Among these, surface layer was cold planned, and HMA overlay treatments were applied to 144 of the projects (733.5 km/455.8 miles), while in 47 projects (197.7 km/122.9 miles) HMA overlay was directly applied to the PCC pavement.

3.3. Acceptance of Projects. Once the candidate projects have been identified, the following criteria have to be met for both the before-treatment (BT) and after-treatment (AT) time-series distress data to accept a pavement section (0.1 mile) within a project for use in the analyses. Any rejected

pavement sections (BT, AT, or both) cannot be used to model pavement performance and are therefore kept away from the analysis.

Criteria 1. One point before treatment (BT acceptance): distress value before treatment is important to identify the effectiveness of the treatment.

Criteria 2. Positive gain in distress based on the best-fit curve (AT acceptance): decrease in the AT distress between the first and the last data points is likely the results of the application of maintenance actions that are not recorded in the available database. When the available AT condition data of a pavement segment produce negative slope/rate of regression model, that segment is excluded from the analyses. Negative regression parameters imply that the distress is "healing" with time, and consequently the service life is infinite.

3.4. Climatic Parameters. Climatic parameters such as temperature and precipitation are the most important environmental factors that have considerable effects on the pavement distress. LADOTD does not have a complete database for climatic data, so it is deemed necessary to make a climatic database for this study. For this purpose, 20 weather stations encompassing Louisiana were selected based on data availability. The selection was made in a way to cover all part of Louisiana. Among the 20 weather stations from the National Climatic Data Center (NCDC), 17 of them were in Louisiana, 2 in Texas, and 1 in Mississippi. Each station's geographical latitude, longitude coordinate, and elevation from mean sea level (MSL) were recorded. For climatic data, daily maximum, minimum, and mean temperature and daily precipitation value from year 2000 to 2010 were collected.

After collecting the climatic data, it was necessary to interpolate data for each control section from nearby weather stations. The geographical latitude and longitude coordinate of each control section's beginning log-mile (BLM) were recorded from LADOTD PMS data, and inverse distance weighting method was used for interpolation. Inverse distance weighting method is based on the assumption that the nearby values of the stations contribute more to the interpolated values than remote observations. The effect of a known data point is inversely related to the distance from the unknown location that is being interpolated. This method is efficient and intuitive, and interpolation works best with evenly distributed points [11]. For each project four nearby weather stations were taken into account for climatic data interpolation. A comprehensive routine was developed using Matrix Analysis Laboratory (MATLAB) software for this analysis.

Most researchers in the past had used freezing index (FI) as one of the parameters for predicting rut model [6, 12]. However, Louisiana's temperature seldom goes below freezing temperature; furthermore based on LTTP the state falls under wet-no-freeze zone. It was also noticed from the climatic data that only few days in a year were below freezing temperature. Hence, for Louisiana, a new Temperature Index (TI) similar to FI is introduced to evaluate the effect of

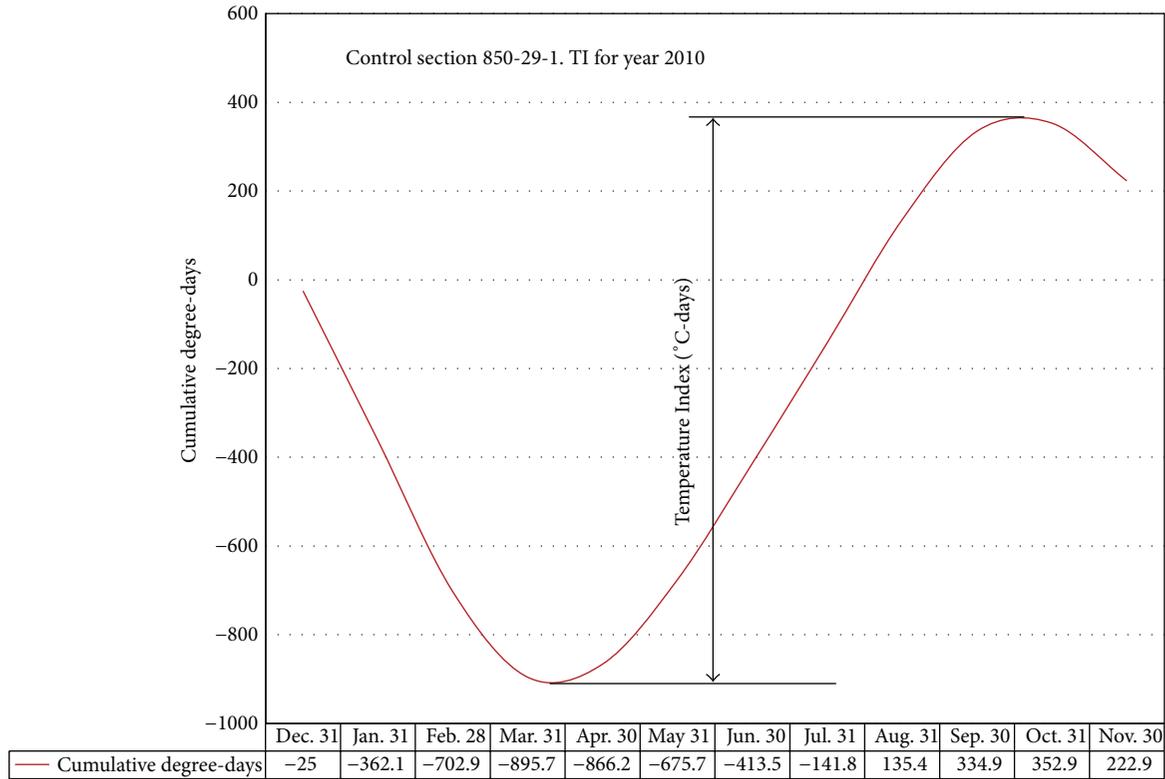


FIGURE 1: Determination of Temperature Index.

temperature [13]. Unlike FI, TI represents the variation of temperature of a particular place over the year. Base temperature of 20°C (68°F) was used to find the TI. A negative one-degree day represents one day with a mean air temperature one degree below 20°C, and a positive one-degree day indicates one day with a mean air temperature one degree above 20°C. The mean air temperature for a given day is the average of high and low temperatures during that day. If the mean air temperature is 25°C on the first day, 22°C on the second, and 17°C third days, the total degree days for the three-day period are $(25 - 20) + (22 - 20) + (17 - 20) = 4$ degree days. The degree days for each month were similarly calculated. A plot of cumulative degree days versus time for control section 850-29-1 for year 2010 was plotted, and it resulted in a curve, as shown in Figure 1. The difference between the maximum and minimum points on the curve during one year is called the Temperature Index for that year.

Although, Louisiana rarely exhibits temperature below 0°C (32°F), there are variations between colder temperature at different regions. Northern regions of Louisiana suffer colder temperature than southern regions. To study the effect of cold temperature, Low Temperature Index (LTI) was utilized in which 4°C (39.2°F) was used as the threshold temperature:

$$LTI = \sum (4 - T_m), \quad T_m \leq 4^\circ\text{C}, \quad (1)$$

where LTI is the Low Temperature Index, (°C-days) in a year, and T_m the mean daily temperature (°C).

For example, project 005-09-0033 is located in District 2 (southern part) and has a LTI value of -13.18 (°C-days) compared to LTI value of 42.79 (°C-days) for project 025-08-0053 which is located in District 4 (northern part) for year 2000. This difference could easily contribute to performance of the pavement and must be considered while producing distress models.

To evaluate the effect of precipitation, a new precipitation index (PI) was introduced in this study. The PI is the product of precipitation/year and number of days/year of precipitation:

$$PI = P \cdot N_p, \quad (2)$$

where PI is the precipitation index (cm-days), P is the precipitation/year (cm), and N_p is the number of days of precipitation in that year.

The PI represents the amount and exposure of pavement to moisture that is responsible for pavement damage in a year.

4. Development of Rutting Model

There are generally three distinct stages for the rutting behavior of pavement materials under a given set of material, load, and environmental conditions, and they are primary, secondary, and tertiary stages [6]. This paper tries to predict the primary and secondary stages behavior as one which follows a concave trend with load repetitions and time which can be modeled as a power function.

So, $Rut = \lambda t^\beta$ can be written as $\ln(Rut) = \ln(\lambda) + \beta \ln t$ which is basis for our regression analysis. Rutting is the result of accumulation of damage due to repeated ESAL (Equivalent Single Axle Load), so the cumulative ESAL was considered in model. Pavement layer thickness is expected to have an important effect on the rut. For the same traffic, climatic and soil conditions increasing the thickness of pavement provide more structural capacity and thus result in lower rut depth. Composite pavement has a layer of Portland Cement Concrete (PCC) underneath the hot mix asphalt (HMA) overlay. For predicting the rut, both of these thicknesses were considered because both of the layers provide structural strength to the pavement. The thickness of overlay treatment is decided based on the condition of pavement before the treatment is applied to the pavement and also the future traffic and site factors such as soil condition, base subbase, and thickness of the PCC. The higher the ratio of HMA/PCC, the less damage pavement should suffer. This concept was used to develop the model. Also, interstates and arterials have more reliability and higher standards than collectors and local road. So, with the increase in functional classification the distress value should increase.

Rutting is expected to vary at different times of the year due to variation in temperatures. Rutting of HMA layers is more common during hot summer months than it is during the winter, and deformation is more likely to happen in wet spring months [1]. But it was found that the temperature and precipitation indices developed for this study do not possess strong statistical significance pertaining to the regression model.

For developing rutting model, 931.3 km of composite pavements were analyzed. However based on the data availability and project acceptance criteria about 541.7 km of data was utilized for regression analyses.

Consider,

$$\ln(Rut) = a_0 + a_1 \cdot \ln(CESAL) + a_2 \cdot \frac{Fn}{(T_{HMA}/T_{PCC})} \cdot \ln(t), \quad (3)$$

where Rut is the average rut depth per lane (cm), $CESAL$ the cumulative ESAL, T_{HMA} the thickness of HMA overlay (cm), T_{PCC} the thickness of PCC layer (cm), Fn the functional classification, and t the age of treatment (year).

After the regression, the final form of the rutting was found to be

$$Rut = \exp\left(\alpha \cdot \left(-5.214 + 0.264 \cdot \ln(CESAL) + 0.053 \cdot \frac{Fn}{(T_{HMA}/T_{PCC})} \cdot \ln(t)\right)\right), \quad (4)$$

where Rut is the average rut depth per lane (cm), and $\alpha = 0.916$ is a calibration factor obtained by minimizing the RMSE value using the above model.

The results of statistical analysis are shown in Table 2. Figure 2 shows the predicted versus the measured $\ln(Rut)$

TABLE 2: Statistics of the regression analysis of Rut model for composite pavement.

Regression statistics				
Multiple R		0.89		
R square		0.79		
Adjusted R square		0.79		
Standard error		0.62		
Observations		364		
F statistics		693.26		
Significance F		2.35×10^{-124}		
Coefficients	Value	Standard error	t-stats	P values
a_0	-5.214	0.302	-17.222	6.01×10^{-49}
a_1	0.264	0.025	10.505	1.05×10^{-22}
a_2	0.0536	0.003	15.246	7.21×10^{-41}

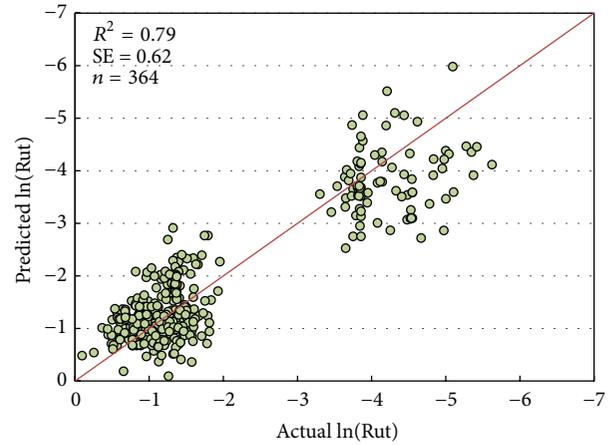


FIGURE 2: Predicted versus actual $\ln(Rut)$ for composite pavement.

values for overlay treatment on composite pavement. It depicts that, with an exception of a few data points, there is a good agreement between the predicted and measured rut values, thus indicating that the model was able to predict the rut reasonably well.

4.1. Incorporation of Existing Pavement Condition for Better Prediction. In order to improve the prediction capabilities of the developed regression model for rutting, the existing pavement condition was incorporated using the following methodology:

$$Rut_{pred} = Rut_{Existing} + \Delta Rut. \quad (5)$$

We know

$$Rut = \exp^{(X)}, \quad (6)$$

where

$$X = a_0 + a_1 \cdot \ln(CESAL) + a_2 \cdot \frac{Fn}{(T_{HMA}/T_{PCC})} \cdot \ln(t). \quad (7)$$

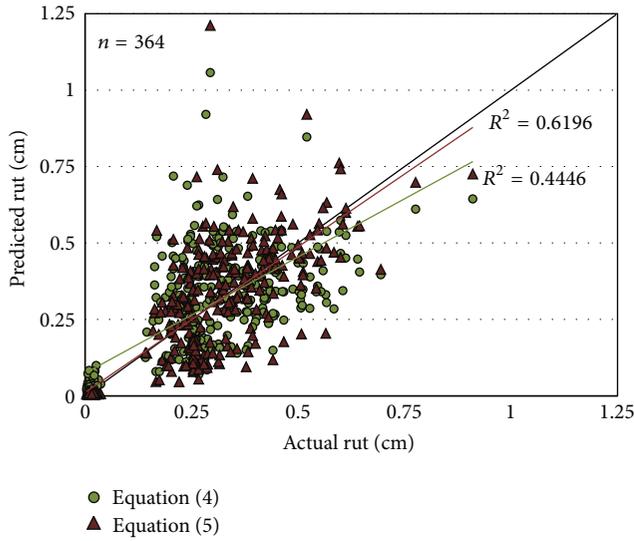


FIGURE 3: Comparison between predicted versus actual rutting using parent model (4) and the model incorporating existing pavement condition (5).

So, first-order derivative of Rut equation with respect to time is as follows:

$$\frac{d(\text{Rut})}{dt} = \exp^{(X)} \cdot \frac{d(X)}{dt} \approx \frac{\Delta \text{Rut}}{\Delta t}, \quad (8)$$

$$\Delta \text{Rut} = \exp^{(X)} \cdot \frac{d(X)}{dt} \cdot \Delta t.$$

Here, $\Delta \text{Rut}/\Delta t$ is the discrete form of the first order derivative and ΔRut the change in rut in one year by putting $\Delta t =$ unit time (years).

Consider,

$$\text{CESAL} = \frac{\text{ESAL}_i (1 + r_{\text{ESAL}})^t - 1}{r_{\text{ESAL}}}, \quad (9)$$

where r_{ESAL} is growth rate of ESAL growth rates obtained from the existing data. ESAL_i is the initial values at the time of treatment and t the surface age (years).

After incorporating ΔRut from (8) in (5), analysis for rutting was conducted. It was found that coefficient of determination (R^2) value significantly improved. Furthermore, the error distribution for between actual and predicted rutting exhibited more normality which is an indicator of a good model.

Figure 3 shows the comparison between actual and predicted values using the regression equations and after incorporation of existing pavement condition. Value of R^2 improved from 0.44 to 0.62. The predicted values show a better scatter along the line of equality when existing pavement condition was incorporated in the model. Figure 4 shows the applicability of the two approaches when plotted against actual rut values of two different projects.

Comparison between actual error distributions of rutting for regression model (4), after assimilation of existing

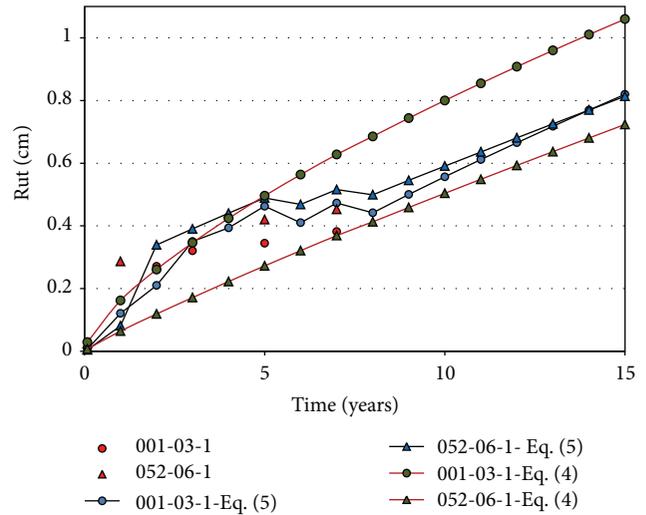


FIGURE 4: Rut Model behavior comparison against actual value of Rut.

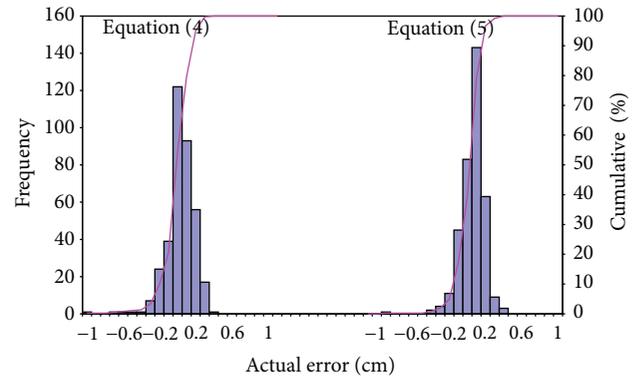


FIGURE 5: Comparison between actual error distribution of rut using parent model (4) and the model incorporating existing pavement condition (5).

pavement condition (5), is shown in Figure 5. For regression equation the error distribution is random and shows normal behavior with exception to few high error values in the distribution. After the incorporation of existing pavement condition, the error distribution exhibited a well-defined bell-shaped curve with more error values laying closer to zero.

5. Conclusions

Rutting behavior of about 931.3 km of composite pavements in the State of Louisiana was analyzed. Based on data availability and project selection criteria about 541.7 km of composite pavements were utilized for developing regression model for rutting. It was found that rutting was largely affected by cumulative ESAL, thickness of the PCC layer, highway functional classification, and surface age. The results of analysis indicated that all the variables showed very strong statistical significance for predicting rutting. It was found that, by incorporating the existing pavement condition,

the predicting ability and reliability of the model were greatly improved. Such model showed significant improvement and may be utilized as a good pavement management tool for predicting the rutting of the overlay treatment for composite pavement, thereby, facilitating timely maintenance and rehabilitation actions.

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