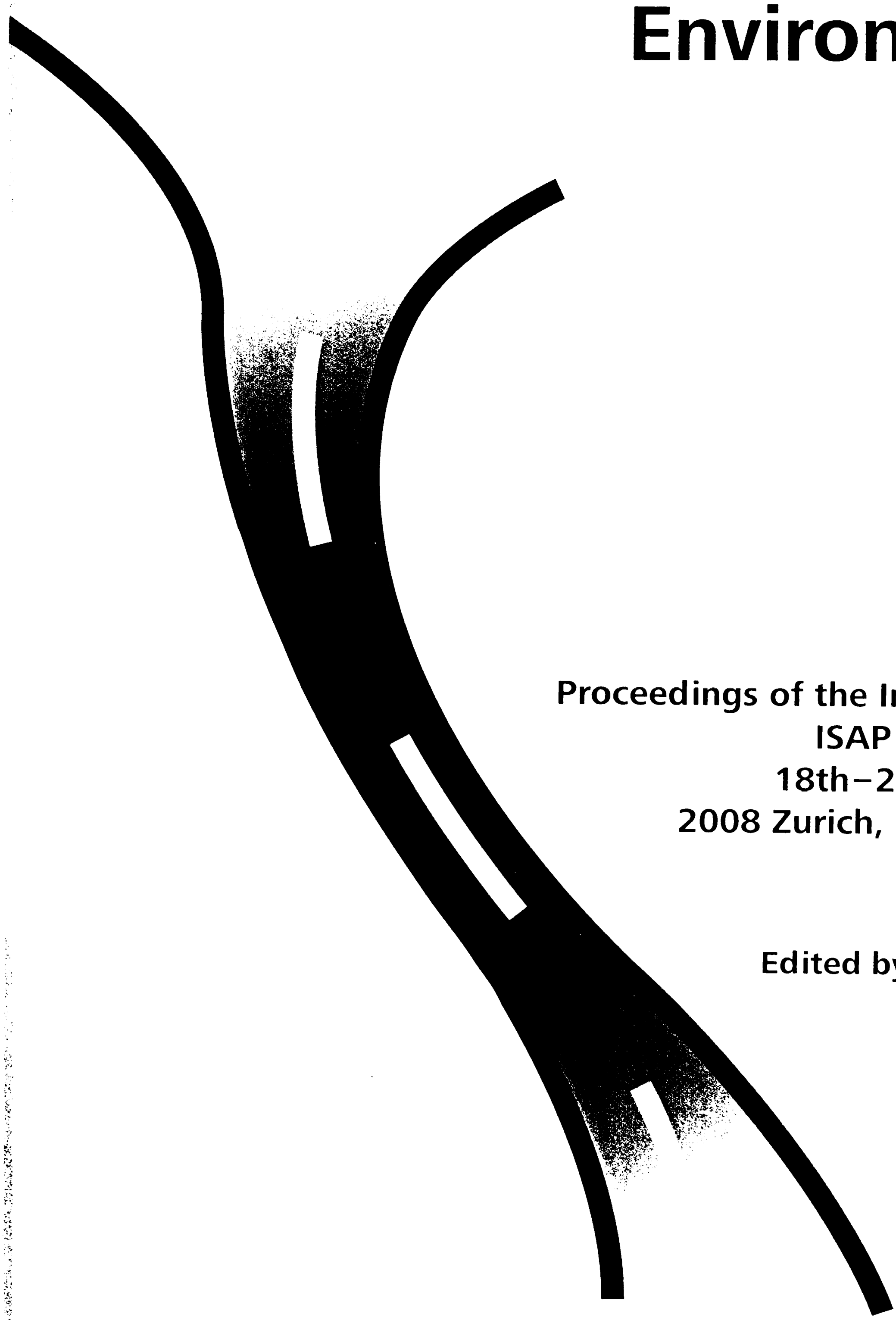
# Asphalt Pavements and Environment



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# International ISAP Symposium on Asphalt Pavements and Environment

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The International Society for Asphalt Pavements (ISAP) is the leading world-wide organization promoting technology transfer for flexible pavements (http://www.asphalt.org). Known for its high quality International Conferences covering a wide spectrum of most actual practical topics and research activities on asphalt pavements, such as the last 10th ISAP Conference 2006 in Quebec, Canada, and the next ISAP Conference 2010 in Nagoya, Japan, ISAP is also initiating and sponsoring International Symposia that are focused on selected topics.

The Symposium ISAP2008 on Asphalt Pavements and Environment, 18th-20th August 2008 in Zurich, Switzerland, was organized by Empa, Swiss Federal Laboratories for Materials Testing and Research and concentrated on the question where and how asphalt pavements can more actively contribute to an environmentally friendly, sustainable development and a more harmonic, resource preserving way of life where roads will continue to play a major role in fulfilling human mobility needs.

Over seventy papers were accepted after rigorous peer-review for presentation and for being printed in the proceedings of ISAP2008. The papers are assigned to the following chapters
Environmental Impact and Managing Resources
Environmentally Sustainable New Materials
Recycling, Repeated Recycling and Material Resources
Energy Saving and Production
Emissions and Noise Reduction
Environmental resistance and durability
Innovative Design
Drainage and Water Susceptibility
Durability and Aging

This book addresses to researchers, practitioners and decision makers with a need and interest to learn about the state of the art as well as the latest environment-related developments and future ideas in asphalt pavement technology. The book also contains original ideas, concepts and practical advice for students and young researchers who are looking for in-depth information on how to achieve more sustainable and environmentally beneficial use of asphalt while meeting new technical, scientific and economic challenges.

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# Development of Rutting Prediction Models for Flexible Pavements Using LTPP Database

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ABSTRACT: This study strives to develop improved rutting prediction models for flexible pavements using the Long-Term Pavement Performance (LTPP) database. The prediction accuracy of the existing prediction models implemented in the recommended Mechanistic-Empirical Pavement Design Guide was found to be inadequate. Exploratory data analysis indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate. Therefore, generalized linear model (GLM) along with several distribution functions were adopted for the modeling process. After considerable amount of trails, the quasi family with the same link and variance functions from Poisson family appeared to be the best choice. To further enhance the model fits, generalized additive model (GAM) techniques were adopted. Box-Cox power transformation technique was utilized to estimate a proper, monotonic transformation for each variable based on the preliminary GAM model. The LTPP pavement performance data was refitted with these transformed predictors using GLM techniques. Consequently, the resulting mechanistic-empirical models included several variables such as yearly KESALs, pavement age, annual precipitation, annual temperature, critical compressive strain on top of subgrade layer, freezing-index, and freeze-thaw cycle. The goodness of fits appeared to better agree with the performance data although their further enhancements are possible and recommended.

## 1. Introduction

Performance predictive models have been used in various pavement design, evaluation, rehabilitation, and network management activities. Since rutting is one of the major flexible pavement distress types primarily caused by the accumulated traffic loads. Extensive research has been conducted to predict the occurrence of this distress type using various empirical and mechanistic-empirical approaches. Conventional predictive models usually correlate rutting damage to the critical compressive strain of the subgrade and the allowable number of load repetitions. As pavement design evolves from traditional empirically based methods toward mechanistic-empirical, the equivalent single axle load (ESAL) concept used for traffic loads estimation is no longer adopted in the recommended Mechanistic-Empirical Pavement Design Guide (MEPDG) (NCHRP Project 1-37A) (1, 2). The success of the new design guide considerably depends upon the accuracy of pavement performance predictions. Thus, this study will first investigate its goodness of fit and strive to develop improved rutting prediction models for flexible pavements using the Long-Term Pavement Performance (LTPP) database (http://www.datapave.com or LTPP DataPave Online) (3, 4, 5).

## 2. Brief review of existing mechanistic-empirical prediction models

Since rutting is primarily caused by accumulated traffic loads, various predictive models as shown in Table 1 based on the following expressions have been proposed to estimate the maximum allowable number of repetitions ($N_d$) using the critical compression strain ($\varepsilon_c$) on top of the subgrade (6-9):

$$N_{d} = k_{4}(\varepsilon_{c})^{k_{5}} \quad (1)$$

In which, $k_4$, and $k_5$ are regression coefficients. Cumulative rutting damage ($D_d$) is then calculated by adding the damage caused by each individual load application based on Miner's hypothesis, where, $k$ is the number of axle load type, $n_i$ is the number of axle applications, and $N_{di}$ is the corresponding maximum allowable number of repetitions.

$$D_{d} = \sum_{i=1}^{k} \frac{n_{i}}{N_{di}} \leq 1.0 \quad (2)$$

**Table 1**: Coefficients for predicting allowable load repetitions

| Organization (Year) | $k_4$ | $k_5$ |
|---|---|---|
| AI (1982) | $1.365\times10^{-9}$ | 4.477 |
| Shell (1994) | $6.15\times10^{-7}$ | 4.0 |
| Indian model (1999) | $2.56\times10^{-8}$ | 4.533 |
| Mn/ROAD (2003) | $7.0\times10^{15}$ | 3.909 |

Starting from 1987, the LTPP program has been collecting a national pavement database in a factorial format with wider ranges of pavement designs, materials, and climatic zones. More than 2,400 asphalt and Portland cement concrete pavement test sections across the North America have been monitored. Very detailed information about original construction, pavement inventory data, materials and testing, historical traffic counts, performance data, maintenance and rehabilitation records, and climatic information have been collected. In the NCHRP project P-020 (10), an early sensitivity analysis study of the LTPP database was conducted and the following models were developed for rutting prediction:

$$\text{Rut Depth} = N^{B}10^{C} \quad (3)$$

in which, Rut Depth is in hiches; N is the accumulated 18-kip equivalent single axle load (ESAL, in thousands), $B = b_o + b_1x_1 + b_2x_2 + \ldots\ldots + b_nx_n$ and $C = c_o + c_1x_1 + c_2x_2 + \ldots\ldots + c_nx_n$. The regression coefficients are given in Table 2. Separate models for different climatic zones (dry-freeze, dry-nonfreeze, wet-freeze, and wet-nonfreeze) are also available.

In the recommended MEPDG (2), the rutting damage is determined in an incremental manner based on more complicated Axle Load Spectra (ALS) concept. The damage is estimated for each subseason of each sublayer. To estimate the permanent deformation (or rut depth) of each sublayer, the plastic strain accumulated at the end of each subseason was computed. The overall permanent deformation is briefly expressed as follows:

$$RD = \sum_{i=1}^{k} \varepsilon_{p}^{i} h^{i} \quad (4)$$

In which, RD is the rut depth (in.); $\varepsilon_{p}^{i}$ is total plastic strain in sublayer i; $h^{i}$ is the thickness of sublayer i; and k is the number of sublayers. The process is repeated for each load level, subseason, and month of the analysis period. Permanent deformation is only estimated for asphalt bound and unbound layers. To estimate the permanent deformanent of asphalt layer the following model was proposed:

$$\frac{\varepsilon_p}{\varepsilon_r} = k_1 * 10^{-3.4488} T^{1.5606} N^{0.479244} \tag{5}$$

**Table 2**: Regression coefficients of the P-020 rutting model

| Parameters xi | Unit | Regression Coefficients bi | Regression Coefficients ci |
|---|---|---|---|
| (Intercept) | - | 0.151 | -0.00475 |
| Log ( HMAC percent passing #4 shieve ) | Weight % | 0 | -0.596 |
| Log ( HMAC air content ) | Voulme % | -0.0726 | 0 |
| Log ( base thickness ) | in. | 0 | 0.190 |
| Subgrade (percent passing #200 shieve) | Weight % | 0 | 0.00582 |
| Freezing Index (FI) | Degree F-Days | 8.49*10-6 | 0 |
| Log ( AC thickness ) × Log ( base thickness ) | in. | 0 | -0.161 |

where, $\varepsilon_p$ is the accumulated plastic strain at N load repetitions; $\varepsilon_r$ is the resilient strain of the asphalt material as a function of mix properties, temperature and time rate of loading; N is the numver of load repetitions; T is temperature (degress F); $k_1$ is a function of total asphalt layer thickness ($h_{ac}$, in.) and depth (in.) to correct for the confinine pressure at different depths as follows:

$$\begin{aligned} k_1 &= (C_1 + C_2 * depth) * 0.328196^{depth} \\ C_1 &= -0.1039 * h_{ac}^2 + 2.4868 * h_{ac} - 17.342 \\ C_2 &= 0.0172 * h_{ac}^2 - 1.7331 * h_{ac} + 27.428 \end{aligned} \tag{6}$$

More detailed information is available in the literature (2). The prediction accuracy of the proposed models implemented in the recommended MEPDG (2) will be further investigated. To avoid undesirable misunderstanding of the new guide's prediction algorithm due to the complexity involved, it was decided to directly use the MEPDG software for the prediction of rutting. The beta version of the software could be downloaded from http://www.trb.org/mepdg/software.htm.

## 3. Database preparation

Initially, the DataPave 3.0 program was used to prepare a database for this study. However, in order to obtain additional variables and the latest updates of the data, the Long-Term Pavement Performance database retrieved from http://www.datapave.com (or LTPP DataPave Online, Release 18.0) (4) became the main source for this study. There are 8 general pavement studies (GPS) and 9 specific pavement studies (SPS) in the LTPP program. Of which, only asphalt concrete (AC) pavements on granular base (GPS1) and on bound base (GPS2) was used for this study.

This database is currently implemented in an information management system (IMS) which is a relational database structure using the Microsoft Access program. Automatic summary reports of the pavement information may be generated from different IMS modules, tables, and data elements. The thickness of pavement layers was obtained from the IMS Testing module rather than the IMS Inventory module to be consistent with the results of Section Presentation module in the DataPave 3.0 program. Several material properties were queried from the Inventory module. Detailed traffic counts and equivalent single axle load (ESAL) were obtained from the Traffic module. The cumulated ESAL during the performance analysis period was calculated by multiplying pavement age with mean yearly ESAL (or kesal) which could be easily estimated from the database. Environmental data were retrieved from the IMS Climate module and the associated Virtual Weather Station (VWS) link. The rutting data used in this study was obtained from MON_T_PROF_INDEX_SECTION table in the IMS Monitoring module. Maintenance and rehabilitation activities could effectively reduce the distress quantities. Thus, the records in both Maintenance and Rehabilitation modules were used to assure that this study only chose the performance data of those sections without or before major improvements.

For the purpose of this study, a Microsoft Excel summary table containing the pavement inventory, material and testing, traffic, climatic, and distress data was created using the relational database features of the Access program. The Excel table was then stored as S-Plus datasets for subsequent analysis. The summary, table, cor, plot, pairs, and coplot functions were heavily utilized to summarize the information of interest and to provide more reliable data for this study. To estimate the critical compressive strain ($\varepsilon_c$) of the subgrade layer, a systematic approach was utilized and implemented in a Visual Basic software package to automatically read in the pavement inventory data from the summary table, generate the BISAR input files, conduct the batch runs, as well as summarize the results (5). In which, the static (or laboratory tested) elastic modulus data recorded in the IMS Testing module and a single wheel load of 40 kN (9,000 lbs) with a tire pressure of 0.482 MPa (70 psi) were used for the analysis.

Furthermore, the aforementioned mechanistic-empirical models also require the dynamic Young's modulus of AC surface layer. LTPP program utilized the MODCOMP4 program to (11-12) backcalculate the dynamic modulus of each pavement layer which could be retrieved from the IMS Monitoring module. Thus, it would be interesting to compare the laboratory tested layer moduli versus the backcalculated dynamic Young's moduli so as to have a better understanding of their associated variability. As shown in Figure 1, the variability of the relationship between the dynamic and the static (or laboratory tested) moduli could not be ignored. The average ratios of which are approximately 2.6, 2.7, 7.3, and 3.4 by eliminating some apparent outliers for AC surface, base, subbase, and subgrade layers, respectively (5).

A data cleaning process must be conducted before any preliminary analysis or regression analysis can be performed. With the help of graphical representation, some rutting data were plotted against surveyed years for each section in the database with additional information displayed. Each section was carefully examined. Two additional codes were assigned to each section to indicate the findings of the examination, i.e., whether the rutting is reasonable according to the distress history, or which year of data is questionable and could be deleted if necessary.

## 4. Preliminary analysis of the rutting database

Univariate data analysis consists of statistical methods for describing the distribution and spread of each individual variable. Some basic descriptive statistics regarding the data range, its variation, and the number of missing values for each individual variable were conducted. Univariate data analysis procedure is often used to investigate the possibility of data errors and potential distribution problem for each variable considered in a regression analysis. A few extreme (or unusual) data points may be identified or deleted from the analysis.

A graph is always far more perceptible than thousands of numbers. A single plot which well describes the spread of the data was created by combining these univariate statistics with a histogram. A correlation matrix of these variables and trimmed correlation matrices show the variable correlations after eliminating a certain portion of influential data points or possible outliers such that more reliable indices of the correlations were conducted. A scatter plot matrix can graphically represent their relationships and scatters. Applying a data smoothing technique (lowess) on the same scatter plot matrix (13-14), the pairwise relationships become clearer and possible data errors may also be easily identified.

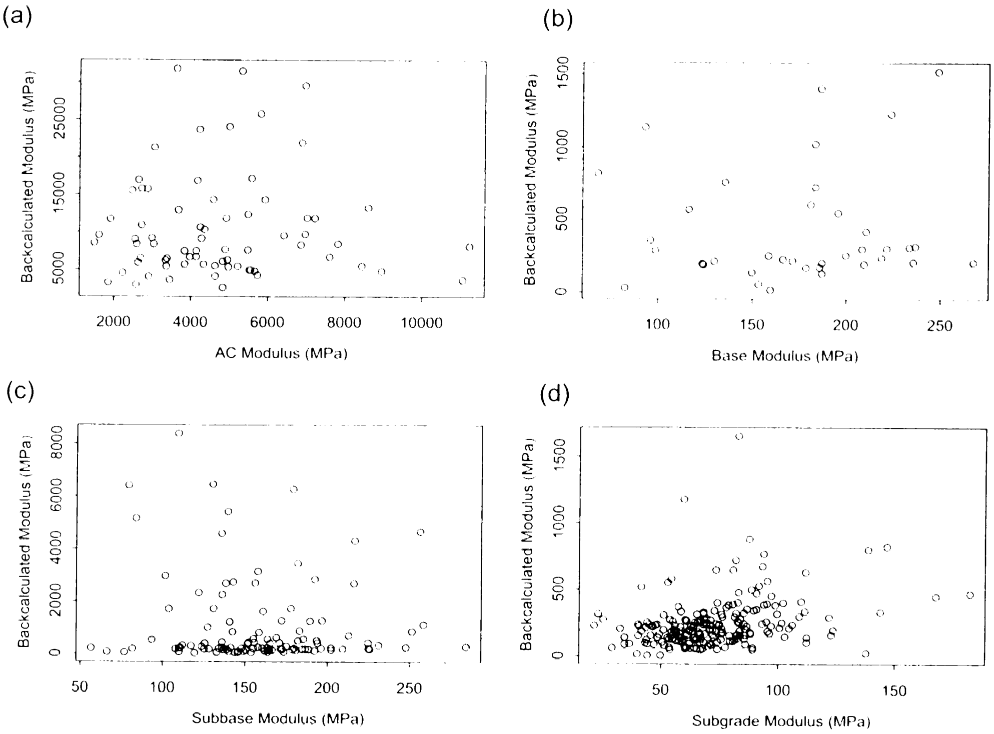


**Figure 1**: Comparison of layer moduli of (a) AC surface layer; (b) base layer; (c) subbase layer; and (d) subgrade obtained from laboratory testing (x axis, MPa) and backcalculation program (y axis, MPa)

## 5. Goodness of prediction of the existing models

To investigate the goodness of prediction, cumulative rutting damage ($D_d$) was calculated and plotted against the actual rutting equations (1) and (2) and the coefficients given in Table 1 for AI and Shell Oil models as shown in Figure 2. In addition, the goodness of prediction using the NCHRP P-020 model and the recommended MEPDG model was given in Figure 3. Unfortunately, the prediction accuracy of the existing prediction models was found to be inadequate.

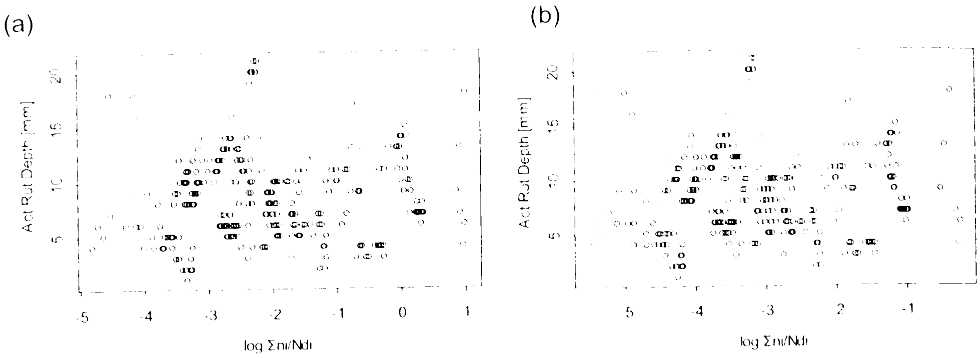


**Figure 2**: Comparison of prediction results using (a) AI model; and (b) Shell Oil model

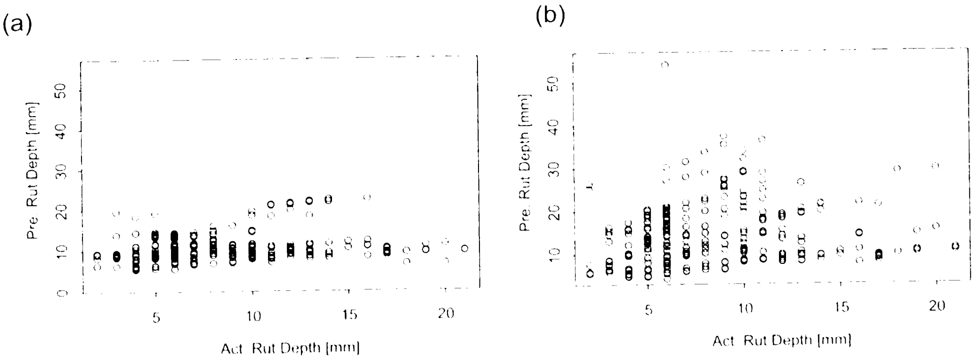


**Figure 3**: Goodness of prediciton using (a) SHRP P-020 model; and (b) MEPDG model

## 6. Development of improved rutting models

The occurrence of rutting in field depends on various factors namely traffic, environment, structure, construction, maintenance and rehabilitation. Even though the use of an incremental approach and more complicated Axle Load Spectra (ALS) concept seems to be a very logical approach, the integration of which with monthly or seasonal environmental factors and several assumed parameters often resulted in more variations in the predictions of rutting due to many uncertainties involved. To develop a more reliable predictive model for practical engineering problems, Lee and Darter (15-16) proposed a predictive modeling approach to incorporate robust (least median squared) regression, alternating conditional expectations, and additivity and variance stabilization algorithms into the modeling process. The robust regression is proposed due to its favorable feature of analyzing highly contaminated data by detecting outliers from both dependent variable and independent variables. Through the iterative use of the combination of these outlier detection and nonparametric transformation techniques, it is believed that some potential outliers and proper functional forms may be identified. Subsequently, traditional regression techniques can be more easily utilized to develop the final predictive model. Nevertheless, many preliminary trials using these regression techniques have shown extreme difficulty to achieve a satisfactory predictive model for this set of data.

### 6.1 Preliminary analysis using linear model

Preliminary analysis using many explanatory parameters in a linear model form was first conducted. The resulting regression statistics are given in Table 3. In which, age stands for pavement age (years); cumulated ESALs (cesal, millions); kesal is the yearly ESALs (thousands); fi is freezing-index (°C-days); temp is mean annual temperature (°C); h1 is the thickness of AC surface layer (cm); base thickness (h2, cm); subgrade resilient modulus (e4, MPa); viscosity of AC binder (visco, poise); precip is mean annual precipitation (mm); L.Damage is the logarithm of rutting damage; epsilon.c ($\varepsilon_c$) is critical compressive strain of the subgrade; and act.rut is actual rutting (mm).

**Table 3**: Regression coefficients of a linear model trail

| Parameters | Value | Std. Error | t value | Pr(>\|t\|) | Parameters | Value | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|---|---|---|---|
| (Intercept) | 13.4420 | 2.7023 | 4.9743 | 0.0000 | visco | 0.0007 | 0.0007 | 0.9741 | 0.3310 |
| age | 0.0191 | 0.0574 | 0.3333 | 0.7392 | fi | -0.0052 | 0.0011 | -4.8267 | 0.0000 |
| cesal | 0.8254 | 0.2251 | 3.2357 | 0.0014 | temp | -0.3344 | 0.0802 | -4.1722 | 0.0000 |
| kesal | -0.0127 | 0.0042 | -3.0422 | 0.0026 | L.Damage | 0.1480 | 0.4436 | 0.3337 | 0.7389 |
| h1 | 0.1385 | 0.0418 | 3.3162 | 0.0010 | epsilon.c | -504.971 | 1264.44 | -0.3994 | 0.6900 |
| h2 | 0.0579 | 0.0193 | 3.0103 | 0.0029 | precip | -0.0019 | 0.0009 | -2.1050 | 0.0363 |
| e4 | -0.0176 | 0.0103 | -1.7189 | 0.0869 | | | | | |
| Residual standard error: 3.493 on 252 degrees of freedom | | | | | | | | | |
| Multiple R-Squared: 0.2245 | | | | | | | | | |

To improve the model fits, it is possible to develop separate models for different climatic zones to account for other factors not considered in the above model implicitly. Due to the unbalanced data structure, of which 80, 114, 194, 71, 141, and 124 data points were obtained from Wet-Freeze, Wet-NonFreeze, Wet, Dry, Freeze, and NonFreeze zones, respectively. A summary report of such analyses is given in Table 4 showing that desireable high coefficient of derermination ($R^2$) might be obtained. Nevertheless, it was also noted that the physical interpretations of many parameters in the model were inappropriate, in which, SEE is the standard error of estimate.

### 6.2 Proposed models using modern regression techniques

Exploratory data analysis of the response variable indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. The Shapiro-Wilk W-statistic for testing for departures from normality was also used to test the distribution of rutting data (13-14). Thus, generalized linear model (GLM) along with several distribution functions including normal/Gaussian, gamma, Poisson, and quasi were adopted for the modeling process. Without fully knowing the error distribution of the response variable, the quasi family with the same link and variance functions from Poisson family was found to be the best choice. After many trails in eliminating insignificant and inappropriate parameters, the resulting mechanistic-empirical model included several variables such as pavement age, yearly ESALs, freezing index, mean annual temperature, and critical compressive strain of the subgrade for rutting prediction.

Since the primary assumption of the above preliminary GLM models is that a linear function of the parameters was used in the model. Generalized additive model (GAM) extends GLM by fitting nonparametric functions using data smoothing techniques to estimate the relationship between the response and the predictors (13). To further enhance the model fits, generalized additive model (GAM) techniques were adopted in this analysis. Box-Cox power transformation technique was routinely utilized to estimate a proper, monotonic transformation for each variable based on the resulting preliminary GAM model. The rutting data was refitted with these transformed predictors using generalized linear model (GLM) techniques. Again, after going through several trails in eliminating insignificant and/or inappropriate parameters, the following model was obtained:

**Table 4**: Summary report of the results of several linear models by different climatic zones

| Zones / Variables | All | Wet-Freeze | Wet-Nonfreeze | Wet | Dry | Freeze | Nonfreeze |
|---|---|---|---|---|---|---|---|
| age | --- | P | --- | P | --- | P | --- |
| cesal | P | --- | P | P | --- | --- | --- |
| kesal | N* | --- | N* | N* | N* | --- | --- |
| h1 | P* | P* | P* | P* | --- | P* | P* |
| h2 | P* | P* | P* | P* | P* | P* | P* |
| e4 | N | N | --- | N | N | --- | --- |
| vicso | --- | N | P* | P* | P* | N | P* |
| fi | N | --- | --- | --- | N | N | --- |
| temp | N* | --- | N* | --- | N* | --- | --- |
| L.Damage | --- | --- | --- | N* | P | P | --- |
| epsilon.c | --- | --- | P | P | --- | N* | P |
| Precip | N* | --- | N* | N* | P | --- | --- |
| No. of Obs. | 265 | 80 | 114 | 194 | 71 | 141 | 124 |
| SEE | 3.493 | 2.689 | 2.399 | 3.259 | 1.381 | 2.344 | 3.215 |
| $R^2$ | 0.2245 | 0.705 | 0.659 | 0.427 | 0.784 | 0.673 | 0.337 |

---: Insignificant; P: Positive correlation; N: Negative correlation; *: Inappropriate.

$$\begin{aligned} \ln(Rut) &= -0.9998 + 0.1370 * \sqrt{age} + 0.3224 * \log(kesal) + 0.3812 * \log(1 + fi) \\ &+ 0.3521 * \sqrt{temp} + 0.08288 * (epsilon.c * 1000)^2 \qquad (7) \\ &\text{Statistics}: R^2 = 0.164, \text{SEE} = 1.22, \text{N} = 265 \end{aligned}$$

in which, dispersion parameter for Poisson family taken to be 1; null deviance = 460.866 on 264 degrees of freedom; residual deviance = 385.5342 on 259 degrees of freedom; *age* stands for pavement age (years); *kesal* is the yearly ESALs (thousands); *fi* stands for annual freezing index ($^{o}$C-days); temp stands for mean annual temperature ($^{o}$C); epsilon.c ($\varepsilon_c$) is the critical compressive strain of the subgrade; Rut is the predicted rutting (mm); and N is the number of observations

Figure 4 shows two diagnosing plots of the above model. The plot of the response versus fitted values also showed that the proposed model has substantial improvements over the existing models in an attempt to uncover the underlying relationships. A normal probability plot or a quantitle-quantile plot of the residuals can be used to check the adequacy of the model. As shown in Figure 4(b), an approximately straight-line relationship was observed indicating that the residuals distribution is close to normal. Since the main objective is to predict the amount of rutting, it is desirable to rearrange the above equation into the following expression and obtain new regression summary statistics:

$$Rut = \exp[-0.99 + 0.137 * \sqrt{age} + 0.322 * \log(kesal) + 0.38 * \log(1 + fi) + 0.352 * \sqrt{temp} + 0.083 * (epsilon.c * 1000)^2] \quad (8)$$

$$\text{Statistics}: R^2 = 0.155, SEE = 3.568, N = 265$$

(a) (b)

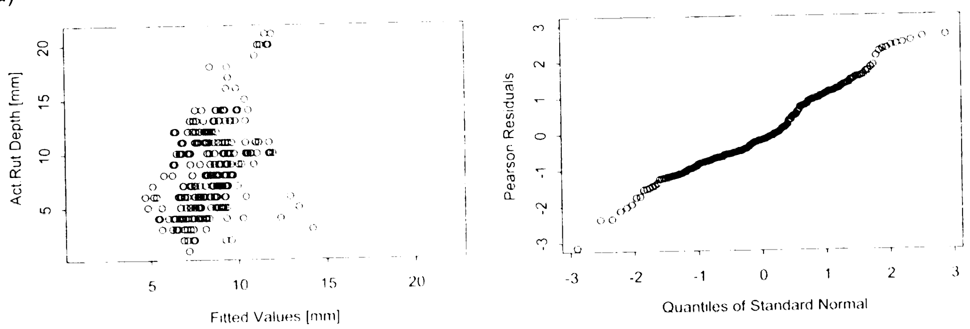


**Figure 4**: Diagnosis plots of the proposed model: (a) response against fitted values; and (b) a normal probability plot of the residuals

To improve the model fits, the following models were subsequently developed for wet and nonfreeze climatic zones, respectively:

$$(Rut)_{wet} = \exp[-1.489 + 0.25 * \sqrt{age} + 0.6 * \log(kesal) + 0.24 * \log(1 + fi) + 0.256 * \sqrt{temp} + 0.288 * (epsilon.c * 1000)^2] \quad (9)$$

$$\text{Statistics}: R^2 = 0.338, SEE = 3.401, N = 194$$

$$(Rut)_{nonfreeze} = \exp[0.253 + 0.065 * \sqrt{age} + 0.486 * \log(kesal) + 0.187 * \log(1 + fi) + 0.06 * \sqrt{temp} + 0.288 * (epsilon.c * 1000)^2] \quad (10)$$

$$\text{Statistics}: R^2 = 0.282, SEE = 3.193, N = 124$$

## 7. Sensitivity analysis of the proposed model

The goodness of the model fit was further examined through the significant testing and various sensitivity analyses of pertinent explanatory parameters. Some plots showing the sensitivity of the various factors in the proposed model are presented in Figure 5. These plots were prepared based on the range of the actual data while setting the remaining parameters to the corresponding mean values. The plots show the relationships among yearly ESAL (kesal, thousands), pavement age (age, years), the critical compressive strain of the subgrade (epsilon.c), mean annual tmperature ($^o$C), yearly freezing index (fi, $^o$C-days), and the predicted rutting (pre.rut, mm). The general trends of these effects seem to be fairly reasonable.

## 8. Conclusions

The prediction accuracy of the existing rutting models for flexible pavements using the Long-Term Pavement Performance (LTPP) database was found to be inadequate and greatly in need for improvement. Normality assumption using conventional regression techniques might not be appropriate for this study. Thus, generalized linear model (GLM) and generalized additive model (GAM) along with the assumption of Poisson distribution and quasi-likelihood estimation method were adopted for the modeling process.

After many trails in eliminating insignificant and inappropriate parameters, the resulting proposed model included several variables such as yearly KESALs, pavement age, annual temperature, critical compressive strain on top of the subgrade, and freezing index for rutting prediction. The goodness of the model fit was further examined. The residual plot and the plot of the response versus fitted values all indicated that the proposed model has substantial improvements over the existing models. Sensitivity analysis of the explanatory variables indicated their general trends seem to be fairly reasonable. The tentatively proposed predictive models appeared to reasonably agree with the pavement performance data although their further enhancements are possible and recommended.

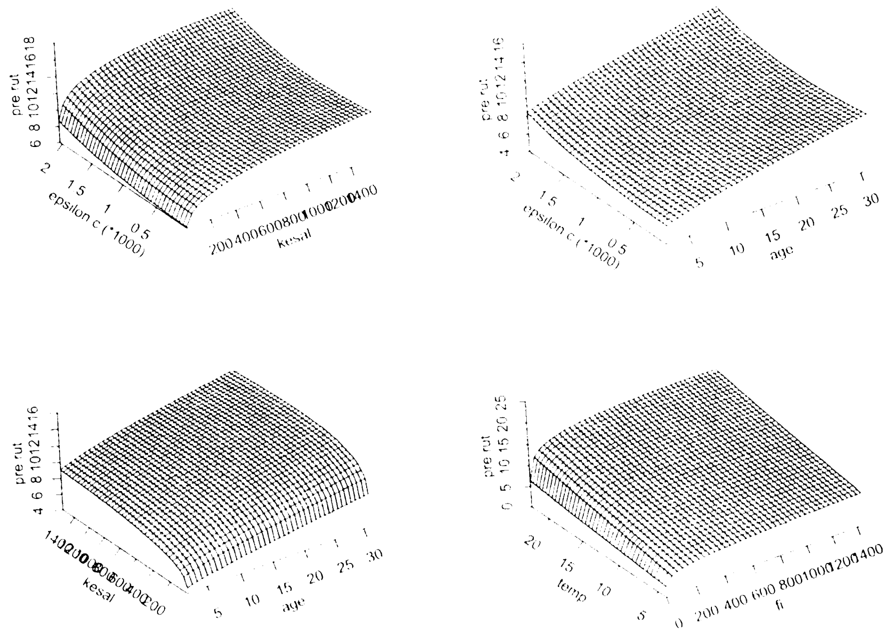


**Figure 5**: Sensitivity analysis of the proposed model

## 9. Acknowledgments

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