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Development of Prediction Models for Joint Faulting using Long-Term Pavement Performance Database

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Abstract: The main objective of this study is to develop improved faulting prediction models for jointed concrete pavements using the Long-Term Pavement Performance (LTPP) database. The retrieval, preparation, and cleaning of the database were carefully handled in a systematic and automatic approach. The prediction accuracy of the existing prediction models implemented in the recommended Mechanistic-Empirical Pavement Design Guide (NCHRP Project 1-37A) was found to be inadequate. Exploratory data analysis of the response variables indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. Therefore, without assuming the error distribution of the response variable, several modern regression techniques including generalized linear model (GLM) and generalized additive model (GAM) along with quasi-likelihood estimation method and Poisson distribution were adopted in the subsequent analysis. Box-Cox power transformation and visual graphical techniques were frequently adopted during the prediction modeling process. By keeping only those parameters with significant effects and reasonable physical interpretations in the model, various tentative performance prediction models were developed. The resulting mechanistic-empirical model included several variables such as pavement age, yearly ESALs, bearing stress, annual precipitation, base type, subgrade type, annual temperature range, joint spacing, modulus of subgrade reaction, and freeze-thaw cycle for the prediction of joint faulting. The goodness of fit was further examined through the significant testing and various sensitivity analyses of pertinent explanatory parameters. The tentatively proposed predictive models appeared to reasonably agree with the pavement performance data although their further enhancements are possible and recommended.

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Key words*: Concrete pavements; Joint faulting; Long-term pavement performance; Modern regression; Prediction models.*

Introduction

Performance predictive models have been used in various pavement design, evaluation, rehabilitation, and network management activities. Faulting is one of the major distress types for jointed concrete pavements primarily caused by the accumulated traffic loads and environmental effects. 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 joint faulting to accumulated traffic, joint types, environmental effects, and several other design parameters [1-3]. 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) [4]. 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 faulting prediction models for jointed concrete pavements using the Long-Term Pavement Performance (LTPP) database (http://www.datapave.com or LTPP DataPave Online) [5-7].

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Review of Existing Mechanistic-Empirical Prediction Models

The NCHRP Project 1-19 [1] was conducted with the primary objective of developing a system for statewide and nationwide evaluation of concrete pavement performance. A total of 410 JPCP and JRCP pavement sections representing 1297 miles of concrete pavement were collected from six states distributed in various climatic regions including Illinois, Georgia, Utah, Minnesota, Louisiana, and California. Eight additional JRCP pavement sections from Nebraska were also included in this database. The combined data represent about six percent of the total Interstate concrete pavements in the continental U.S. Several combinations of multiple regression, stepwise regression, and nonlinear regression techniques were used to develop various pavement performance prediction models using the SPSS statistical package.

However, field-collected pavement database may not contain a wide range of design parameters which may limit the inference space and the results of data interpretation. To remedy this problem, 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 Strategic Highway Research Program Project 393 (SHRP-P-393) [2], an early sensitivity analysis study of the LTPP database was conducted and the following models were developed for the prediction of joint faulting:

$$\begin{aligned} FAULTD = {} & CESAL^{0.25} * \left[0.0238 + 0.0006 * \left(\frac{JTSPACE}{10}\right)^2 \right. \\ & + 0.0037 * \left(\frac{100}{KSTATIC}\right)^2 + 0.0039 * \left(\frac{AGE}{10}\right)^2 \\ & \left. - 0.0037 * EDGESUP - 0.0218 * DOWEL \right] \\ & Statistics\ N = 59, R^2 = 0.534, SEE = 0.028 \end{aligned} \tag{1}$$

$$\begin{aligned} FAULTND = {} & CESAL^{0.25} * \left[-0.07575 + 0.0251 * \sqrt{AGE} + 0.0013 \right. \\ & \left. * \left(\frac{PRECIP}{10}\right)^2 + 0.0012 * \left(FI * \frac{PRECIP}{1000}\right) - 0.0378 * DRAIN \right] \\ & Statistics\ N = 25, R^2 = 0.55, SEE = 0.047 \end{aligned} \tag{2}$$

in which, FAULTD is the average joint faulting (in.) for dowelled jointed pavements; CESAL is the accumulated 18-kip ESALs (millions); JTSPACE is the average transverse joint spacing (ft); KSTATIC is the modulus of subgrade reaction (psi/in.); AGE is the pavement age (years); EDGESUP represents edge support (l for concrete shoulders; 0 for AC shoulders); DOWEL is the dowel diameter (in.); FAULTND is the average joint faulting (in.) for nondowelled jointed pavements; PRECIP is the average annual precipitations (in.); FI is the freeze index (^{o}F-days); and DRAIN is for drainage type. Also note that N is the number of observations; R^2 is the coefficient of determination, and SEE is the standard error of estimates.

Based on the results of NCHRP 1-30 verification study using the LTPP database, the 1998 AASHTO supplemental guide for rigid pavement structure and joint designs adopted the following two faulting models for dowelled and nondowelled jointed pavements, respectively:

$$\begin{aligned} FAULTD = {} & CESAL^{0.25} * [0.0628 - 0.0628 * C_d + 0.3673 * 10^{-8} * BSTRESS^2 \\ & + 0.4116 * 10^{-5} * JTSPACE^2 + 0.7466 * 10^{-9} * FI^2 * PRECIP^{0.5} \\ & - 0.009503 * BASE - 0.01917 * WIDENLANE \\ & + 0.0009217 * AGE] \\ & Statistics\ N = 146, R^2 = 0.6, SEE = 0.022 \end{aligned} \tag{3}$$

$$\begin{aligned} FAULTND = {} & CESAL^{0.25} * \left[0.2347 - 0.1516 * C_d \right. \\ & - 0.00025 * {h_{PCC}}^2 / JTSPACE^{0.25} - 0.0115 * BASE + \\ & 0.7784 * 10^{-7} * FI^{1.5} * PRECIP^{0.25} - 0.002478 * DAYS90^{0.5} \\ & \left. - 0.0415 * WIDENLANE \right] \\ & Statistics\ N = 131, R^2 = 0.45, SEE = 0.034 \end{aligned} \tag{4}$$

where, C_d is the modified AASHTO drainage coefficient; BSTRESS is the calculated maximum concrete bearing stress based on the following closed-form solutions (psi); BASE is for base type (0 for unstabilized base, 1 for stabilized base); WIDENLANE is 0 if not widened or 1 if widened; h_{PCC} is the slab thickness (in.); and DAYS90 is the number of days with maximum temperature above 90°F. The other remaining parameters are defined the same as before [3]:

$$\begin{aligned} & BSTRESS = f_d \times P \times T \left[\frac{K_d(2 + BETA \times OPENING)}{4 \times E_S \times I \times BETA^3}\right] \\ & BETA = \sqrt[4]{\frac{K_d \times DOWEL}{4 \times E_S \times I}} \\ & OPENING = 12 \times CON \times JTSPACE \times \left(\frac{ALPHA \times TRANGE}{2 + e}\right) \end{aligned} \tag{5}$$

in which, f_d is the distribution factor, $f_d = 2 \times 12/(\ell + 12)$. P is the applied wheel load, set to 9000 lbs; T is percent transferred load, set to 0.45; K_d is the modulus of dowel support, set to $1.5\text{x}10^6$ psi/in (405 MPa/mm); BETA is the relative stiffness of the dowel-concrete system; OPENING is average transverse joint opening (in.); E_s is the modulus of elasticity of the dowel, set to $29\text{x}10^6$ psi; I is the moment of inertia of dowel bar cross section (in^4), $I = 0.25\pi * (DOWEL/2)^4$; ℓ is the radius of relative stiffness (in.), $\ell = [Eh^3/(12*(1-\mu^2)k)]^{0.25}$; h is the slab thickness (in.); μ is the Poisson's ratio of the slab; k is the modulus of subgrade reaction (psi/in); CON is the adjustment factor due to base/slab frictional restraint, 0.65 if stabilized base or 0.80 if aggregare base or lean concrete base with bond breaker; ALPHA is the PCC thermal expansion coefficient, set to 0.000006/°F; TRANGE is the annual temperature range (°F); and e is the PCC drying shrinkage coefficient, set to 0.00015 strain. With better drainage in coarse-grained soil or base type, the possibility of pumping and loss of support are reduced and so does the occurrence of joint faulting. Sensitivity analysis of various parameters in the aforementioned models might be conducted.

In the recommended MEPDG [4], the transverse joint faulting for JPCP is determined in an incremental manner based on more complicated Axle Load Spectra (ALS) concept [8]. A faulting increment is determined each month and its magnitude is affected by the current faulting level. The faulting at each month is determined as a sum of faulting increments from all previous months. No prediction model was proposed for JRCP pavements. Various artificial neural networks models were developed based on the ISLAB2000 finite element model to compute critical stresses and deflections. Monthly faulting increment is computed for different axle loads, load positions, and equivalent temperature differences over the analysis period. Traffic data is further processed to determine equivalent number of single, tandem, and tridem axles. Hourly pavement temperature profiles generated from the Enhanced Integrated Climate Model (EICM) is converted to monthly equivalent linear temperature differentials. Monthly relative humidity data is used to account for the effects of seasonal changes in moisture conditions on differential shrinkage and is also converted to effective temperature differentials. The joint load transfer efficiency (LTE) adjustment factor is also determined monthly. The proposed model is briefly summarized as follows:

$$\begin{aligned} & Fault_m = \sum_{i=1}^{m} \Delta Fault_i \\ & \Delta Fault_i = C_{34} * (FAULTMAX_{i-1} - Fault_{i-1})^2 * DE_i \\ & FAULTMAX_i = FAULTMAX_0 + C_7 * \sum_{j=0}^{m} DE_j * Log(1 + C_5 * 5^{EROD})^{C_6} \\ & FAULTMAX_0 = C_{12} * \delta_{curling} * \left[Log(1 + C_5 * 5^{EROD}) * Log\left(\frac{P_{200} * WetDays}{P_s}\right)\right]^{C_6} \end{aligned} \tag{6}$$

in which, $Fault_m$ is the mean joint faulting at the end of month m (in.); $\Delta Fault_i$ is the incremental change (monthly) in mean transverse joint faulting during month i (in.); $FAULTMAX_i$ is the maximum mean transverse joint faulting for month i (in.); $FAULTMAX_0$ is the initial maximum mean transverse joint faulting (in.); *EROD* is the base/subbase erodibility factor; DE_i is the differential deformation energy accumulated during month i.; *EROD* is the base/subbase erodibility factor; $\delta curling$ is the maximum mean monthly slab corner upward deflection PCC due to temperature curling and moisture warping; P_S is the overburden on subgrade (lbs); P_{200} is the percent subgrade material passing #200 sieve; *WetDays* is the average annual number of wet days (greater than 0.1 in. rainfall). C_1 through C_7, C_{12}, and C_{34} are national calibration constants; *FR* is base freezing index defined as percentage of time the top base temperature is below freezing (32°F) temperature [9].

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) [6] 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 jointed plain concrete pavements (GPS3) and jointed reinforced concrete pavements (GPS4) were 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 other material properties such as the percent passing no. 200 sieve 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 kesalpyr) which was estimated from the database. Environmental data were retrieved from the IMS Climate module and the associated Virtual Weather Station (VWS) link. The modulus of each pavement layer backcalculated using the ERESBACK 2.2 program [10] was retrieved from the IMS Monitoring module. The laboratory tested layer moduli were compared with the backcalculated moduli so as to have a better understanding of their associated variability in this study. The variability of the relationship between the laboratory tested (or static) and backcalculated (or dynamic) moduli could not be ignored [7, 11]. The average ratios of backcalculated versus laboratory tested moduli are approximately 1.4, 1.5, and 1.5 for surface, subbase, and subgrade layers for dense liquid foundation, respectively. In addition, the average ratios are roughly 1.0, 1.1, and 3.0 for surface, subbase, and subgrade layers for elastic solid foundation, respectively [7, 11]. For consistency reasons, the recommendation of dividing the backcalculated modulus of subgrade reaction (or k-value) by 2 as the static k-value was used.

The transverse joint faulting data was obtained from MON_DIS_JPCC_FAULT_SECT 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 [12] for subsequent analysis. The summary, table, cor, plot, pairs, and coplot functions were heavily utilized to summarize the information of interest for this study.

A data cleaning process must be conducted before any preliminary analysis or regression analysis can be performed. With the help of graphical representation, joint faulting data were plotted against surveyed years for each section in the database with additional information displayed. For example, a plot as shown in Fig. 1 was used to examine the distress trends in order to identify possible data errors. The state code, SHRP identification number, joint spacing (m), dowel diameter (mm), construction year, and mean yearly ESAL (thousands) are labeled in each plot, respectively. Each section was carefully examined. Two additional codes were assigned to each section to indicate the findings of the examination, i.e., whether the joint faulting is reasonable according to the distress history, or which year of data is questionable and could be deleted if necessary. For example, comparing the first three data points of pavement section 28/4024 with the remaining data, it was found that this section probably had some maintenance or rehabilitation

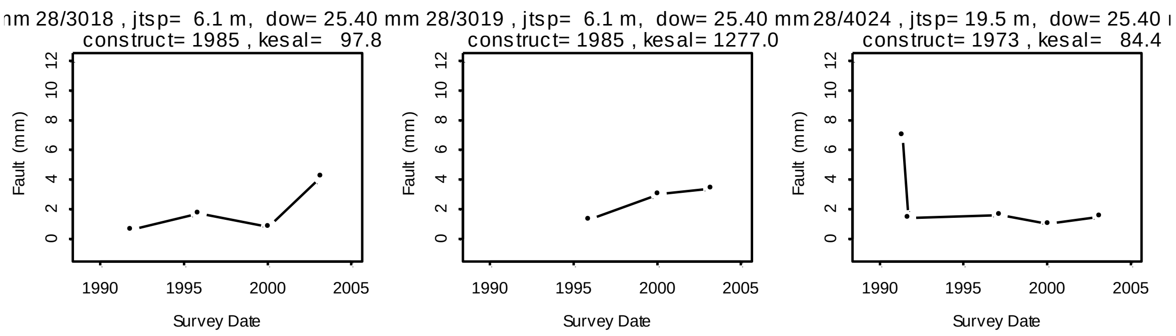


Fig. 1. Faulting History of Some Dowelled Jointed Pavements.

activities although not recorded in the database. Data correction and preparation were made in a way that could be easily traced back. By doing so, different subsets of the final database providing more reliable data might be analyzed for different purposes.

Preliminary Analysis of the Joint Faulting Database

Univariate Data Analysis

Univariate data analysis consists of statistical methods for describing the distribution and spread of each individual variable. Some basic descriptive statistics of dowelled faulting regarding the data range, its variation, and the number of observations for each individual variable are given in Table 1. Univariate data analysis procedure is often used to investigate the possibility of data errors and potential distribution problem for each variable considered. A few extreme (or unusual) data points may be identified or deleted from the analysis. In which, age stands for pavement age (years); kesalpyr is yearly ESALs (thousands); jtspace is joint spacing (m); bstress is the maximum bearing stress (MPa); hpcc is slab thickness (cm); fi is yearly freezing index (^{o}C-days); precip is mean annual precipitation (mm); kstatic is the modulus of subgrade reaction (MPa/m); days32 is the number of days temperature above 32 ^{o}C; trange is the difference of maximum and minimum mean annual

Table 1. Univariate Statistics and Multiple Correlations of Dowelled Jointed Pavements.

(a) Univariate Statistics:

	N	MEAN	STD DEV	SUM	MIN	MAX
age	305	17.51	6.25	5341.10	2.34	33.70
kesalpyr	305	387.28	421.72	118121.35	43.67	2501.62
jtspace	305	10.24	5.24	3122.98	3.96	30.48
bstress	305	21.31	36.35	6499.35	7.34	224.55
hpcc	305	24.65	2.68	7517.64	16.26	33.53
fi	305	212.96	302.88	64954.27	0.00	1270.79
precip	305	1144.74	290.76	349144.39	231.25	1650.60
kstatic	305	65.31	30.61	19919.49	24.05	156.11
days32	305	45.43	34.40	13856.62	1.00	174.35
trange	305	12.03	1.38	3670.31	9.88	17.40
ft	305	62.46	32.24	19050.90	1.61	143.87
act.fault	305	1.04	1.45	316.50	0.00	11.10

(b) Correlation Matrix:

	age	kesalpyr	jtspace	bstress	hpcc	fi	precip	kstatic	days32	trange	ft	act.fault
age	1.00	-0.03	0.37	-0.18	0.02	0.00	0.12	-0.06	-0.03	-0.11	-0.03	0.44
kesalpyr	-0.03	1.00	0.03	0.06	0.13	-0.07	-0.28	0.01	0.20	0.40	0.04	0.13
jtspace	0.37	0.03	1.00	-0.06	0.09	-0.13	0.29	-0.01	0.07	-0.20	-0.12	0.27
bstress	-0.18	0.06	0.06	1.00	-0.12	0.00	-0.19	-0.18	0.08	0.16	0.16	-0.03
hpcc	0.02	0.13	0.09	-0.12	1.00	-0.26	0.26	0.23	0.23	-0.17	-0.26	-0.01
fi	0.00	-0.07	-0.13	0.00	-0.26	1.00	-0.50	-0.13	-0.63	-0.21	0.59	-0.03
precip	0.12	-0.28	0.29	-0.19	0.26	-0.50	1.00	-0.05	0.21	-0.39	-0.58	0.14
kstatic	-0.06	0.01	-0.01	-0.18	0.23	-0.13	-0.05	1.00	-0.01	-0.02	-0.03	-0.15
days32	-0.03	0.20	0.07	0.08	0.23	-0.63	0.21	-0.01	1.00	0.41	-0.79	0.01
trange	-0.11	0.40	-0.20	0.16	-0.17	-0.21	-0.39	-0.02	0.41	1.00	0.11	0.11
ft	-0.03	0.04	-0.12	0.16	-0.26	0.59	-0.58	-0.03	-0.79	0.11	1.00	0.01
act.fault	0.44	0.13	0.27	-0.03	-0.01	-0.03	0.14	-0.15	0.01	0.11	0.01	1.00

(c) Trimmed Correlation Matrix (Deleted 3 Percent of the Data):

	age	kesalpyr	jtspace	bstress	hpcc	fi	precip	kstatic	days32	trange	ft	act.fault
age	1.00	-0.08	0.40	-0.01	0.03	0.03	0.07	-0.08	-0.02	-0.08	-0.03	0.43
kesalpyr	-0.08	1.00	0.13	0.10	0.23	0.11	-0.16	0.05	-0.03	0.41	0.21	0.28
jtspace	0.40	0.13	1.00	-0.09	0.16	-0.10	0.25	-0.03	0.19	-0.09	-0.14	0.16
bstress	-0.01	0.10	-0.09	1.00	-0.34	0.05	-0.08	-0.05	0.13	0.34	-0.01	0.47
hpcc	0.03	0.23	0.16	-0.34	1.00	-0.18	0.33	0.19	0.27	-0.14	-0.33	-0.09
fi	0.03	0.11	-0.10	0.05	-0.18	1.00	-0.65	-0.02	-0.65	-0.12	0.65	0.19
precip	0.07	-0.16	0.25	-0.08	0.33	-0.65	1.00	-0.04	0.53	-0.19	-0.75	-0.08
kstatic	-0.08	0.05	-0.03	-0.05	0.19	-0.02	-0.04	1.00	0.04	0.02	-0.03	-0.04
days32	-0.02	-0.03	0.19	0.13	0.27	-0.65	0.53	0.04	1.00	0.32	-0.84	-0.05
trange	-0.08	0.41	-0.09	0.34	-0.14	-0.12	-0.19	0.02	0.32	1.00	0.10	0.24
ft	-0.03	0.21	-0.14	-0.01	-0.33	0.65	-0.75	-0.03	-0.84	0.10	1.00	0.11
act.fault	0.43	0.28	0.16	0.47	-0.09	0.19	-0.08	-0.04	-0.05	0.24	0.11	1.00

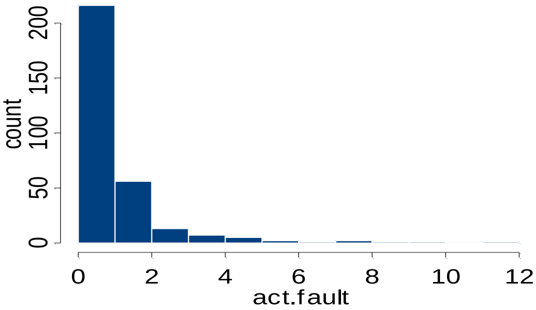


Fig. 2. Exploratory Data Analysis: Dowelled Joint Faulting.

temperature (°C); ft is yearly freeze-thaw cycle; and act.fault is the mean joint faulting (mm).

A graph is far more perceptible than thousands of numbers. A single plot which well describes the spread of the data may be created by combining these univariate statistics with a histogram. A simplified distribution plot which graphically displays the variability of data including median, lower and upper quantiles, 95 percent confidence intervals, and extreme points (if any) may be made in a boxplot. A boxplot displays not only the location and spread of the data but also the skewness as well. A histogram only displays a rough and crude shape of the distribution of data. The distribution of joint faulting of dowelled pavements revealing a relatively skewed distribution is shown in Fig. 2.

Bivariate and Multivariate Analysis

A correlation matrix of these variables is also given in Table 1. In addition, trimmed correlation matrices show the variable correlations after a certain portion of influential data points or possible outliers are eliminated (say 3 percent in this example) such that more reliable indices of the correlations are obtained. Note the difference between the resulting traditional correlation matrix and trimmed correlation matrix. A scatter plot matrix can graphically represent their relationships and scatters. Applying a data smoothing technique (lowess) on the same scatter plot matrix, the pairwise relationships as shown in Fig. 3 become clearer and possible data errors may also be identified.

Investigation of the Goodness of Fit of the Existing Models

To investigate the goodness of predictions, the aforementioned predictive models given in Eqs. (1) to (4) were used to predict the occurrence of joint faulting and the results were plotted against the actual observed data. Fig. 4(a)-(b) shows the goodness of prediction using SHRP-P-393 models for dowelled and nondowelled jointed pavements, respectively. Similarly, Fig. 5(a)-(b) depicts the results of this comparison using 1998 AASHTO models for dowelled and nondowelled jointed pavements. Visual graphical techniques such as condition plots were used to assist in the identification of the factors affecting the goodness of predictions. For example, the observations with relatively high bearing stress and faulting predictions were eliminated from the analysis due to their dowel bar diameters are smaller than 25.4 mm.

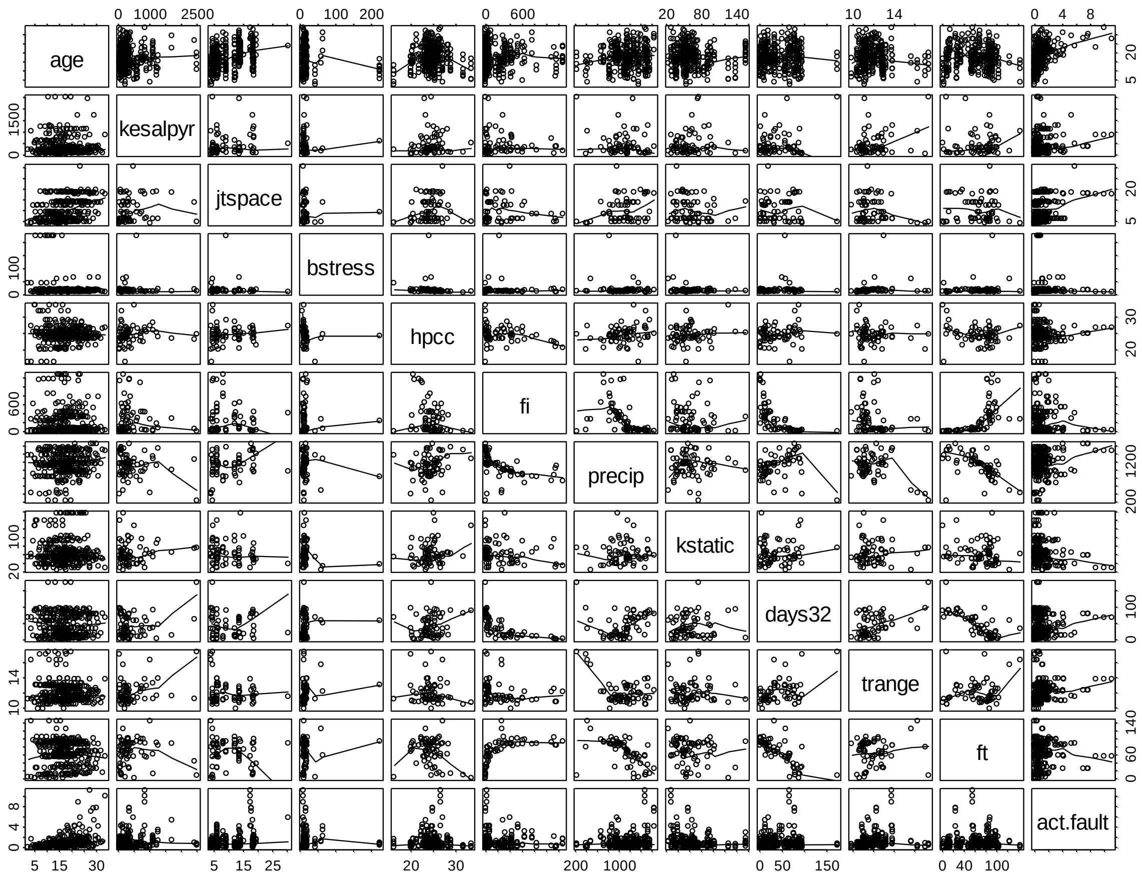
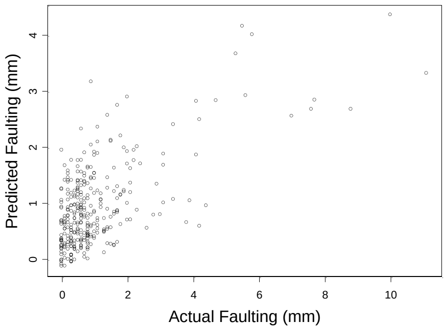
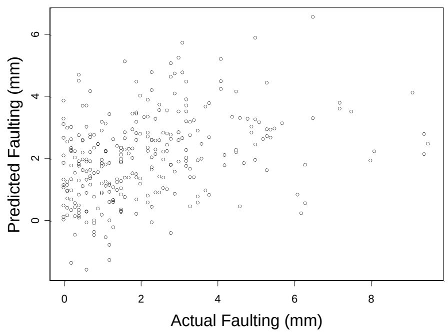


Fig. 3. Scatter Plot Smoother and Matrix for Dowelled Jointed Pavements.

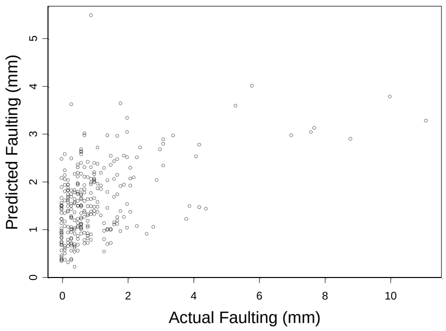


(a)

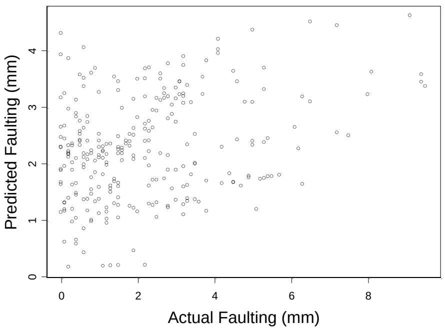


(b)

Fig. 4. Goodness of Prediction Using SHRP-P-393 (a) Dowelled; and (b) Nondowelled Models.



(a)



(b)

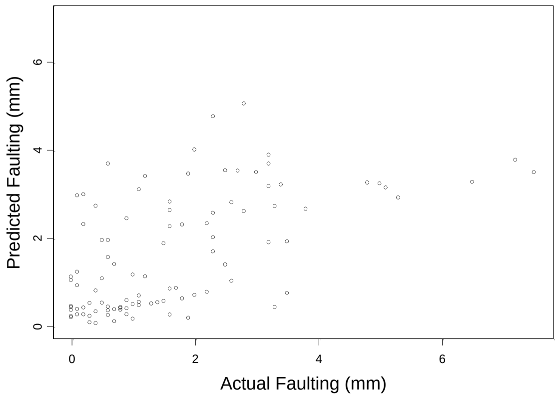
Fig. 5. Goodness of Prediction Using 1998 AASHTO (a) Dowelled; (b) Nondowelled Models.

The prediction accuracy of the proposed models implemented in the recommended MEPDG (*4*) was 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 transverse joint faulting. The beta version of the software could be downloaded from http://www.trb.org/mepdg/ software.htm. A total of 23 dowelled and nondowelled JPCP pavement sections containing 98 data points were randomly selected for this analysis. The goodness of prediction using the SHRP-P-393 models, the 1998 AASHTO models, as well as the recommended MEPDG models is shown in Fig. 6(a)-(c). Unfortunately, the prediction accuracy of the existing prediction models was found to be inadequate.

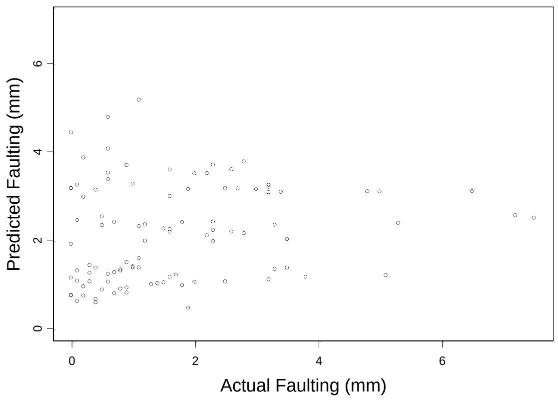
Development of Improved Joint Faulting Models

The occurrence of joint faulting 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 logical approach, the integration of which with monthly or seasonal environmental factors such as humidity and temperature differentials often resulted in more variations in the predictions of joint faulting due to many uncertainties involved. To develop a more reliable predictive model for practical engineering problems, Lee and Darter [13] 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 was 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 was believed that some potential outliers and proper functional forms might be identified. Subsequently, traditional regression techniques can be more easily utilized for model development. Nevertheless, it has been extremely difficult to achieve a satisfactory predictive model for this set of data by using these regression techniques in many preliminary trials.

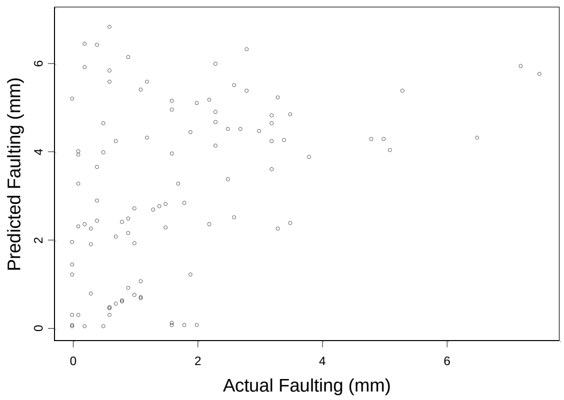
Exploratory data analysis of the response variable as shown in Fig. 2 has indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. The distribution of joint faulting was tested for departures from normality using Shapiro and Wilk's W-statistic [12]. Various transformations including logarithm of the joint faulting were tested. The W-statistic indicated that joint faulting is not lognormal distributed either. Thus, without assuming the error distribution of the response variable, generalized linear model (GLM) [14] along with quasi-likelihood estimation method and Poisson distribution were adopted in the subsequent analysis. Many factors including age, kesalpyr, cesal, jtspace, bstress, hpcc, fi, precip, kstatic, days32, trange, ft, dowel, basetype, edgesup. drain, and stype were considered in the beginning trial analysis. In which, basetype represents base types (0 for granular base, 1 for treated base); edgesup is 0 for AC shoulder and 1 for concrete shoulder; drain is 1 if longitudinal drain and 0 if others; and stype is 1 for A1-A3 coarse-grained soil, 0 for A4-A7 fine-grained soil. By keeping only



(a)



(b)

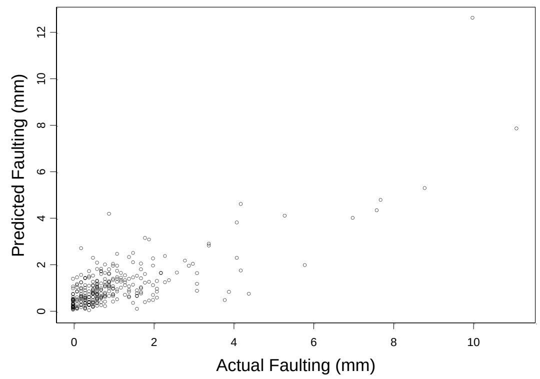


(c)

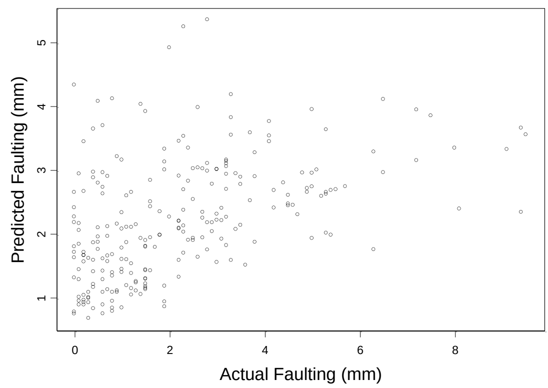
Fig. 6. Goodness of Prediction Using (a) SHRP-P-393; (b) AASHTO 1998; and (c) DG2002 Models.

those parameters with significant effects and reasonable physical interpretations in the model, various tentative prediction models were developed.

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 [15]. To further enhance the model fits, GAM techniques were adopted in the subsequent analysis. Box-Cox power transformation technique was routinely utilized to estimate a proper, monotonic transformation for each variable based on the resulting preliminary



(a)



(b)

Fig. 7. Goodness of Fit of the Proposed (a) Dowelled; and (b) Nondowelled Models.

GAM model. The joint faulting data was refitted with these transformed predictors using GLM techniques. Visual graphical techniques as well as the systematic statistical and engineering approach proposed by Lee and Darter [13] were frequently adopted during the modeling process. After considerable amount of trails, the following preliminary models were developed for faulting predictions of dowelled and nondowelled pavements, respectively. As shown in Fig. 7, a plot of the observed versus the fitted values is provided to illustrate the goodness of the fit.

$$\begin{aligned} FaultD = exp[&1.982 + 0.8413 * \sqrt{age} - 6.094 * \frac{1}{\sqrt{kesalpyr}} \\ &- 1.899 * \frac{1}{\sqrt{bstress}} + 0.05487 * \sqrt{precip} - 0.5103 * basetype \\ &- 0.3309 * stype - 22.35 * \frac{1}{\sqrt{trange}}] \end{aligned} \tag{7}$$

$$Statistics\ N = 305, R^2 = 0.6039, SEE = 0.9122$$

$$\begin{aligned} FaultND = exp[&1.775 - 3.129 * \frac{1}{\sqrt{age}} + 0.01487 * \sqrt{kesalpyr} \\ &- 8.267 * \frac{1}{jtspace} + 0.0004246 * precip \\ &+ 5.530 * \frac{1}{\sqrt{kstatic}} - 0.4735 * basetype + 0.005457 * ft] \end{aligned} \tag{8}$$

$$Statistics\ N = 243, R^2 = 0.2154, SEE = 1.778$$

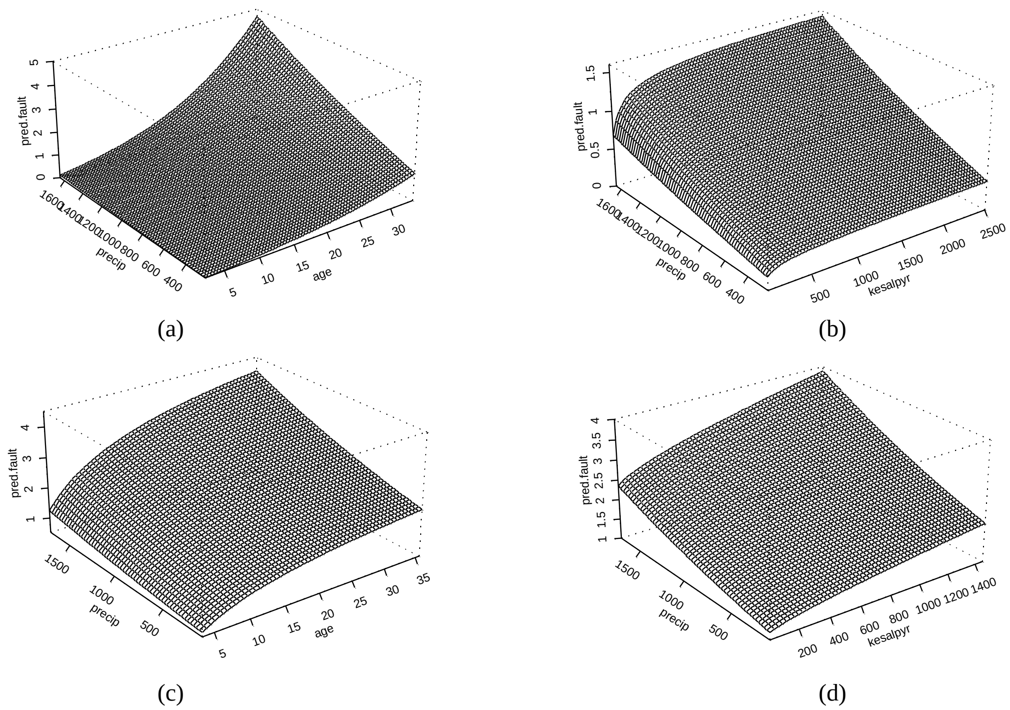


Fig. 8. Sensitivity Analysis of the Proposed Model for: (a)-(b) Dowelled; and (c)-(d) Nondowelled Jointed Pavements.

Sensitivity Analysis of the Tentatively Proposed Models

The goodness of the model fit was further examined through significant testing and various sensitivity analyses of pertinent explanatory parameters. Some plots showing the sensitivity of various factors in the tentatively proposed models are presented in Fig. 8. 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 ESALs (kesalpyr, thousands), pavement age (age, years), annual precipitation (precip, mm), and the prediction of joint faulting (pred.fault, mm). The general trends of these effects seem to be fairly reasonable.

Discussions and Conclusions

Even though the use of an incremental approach and more complicated Axle Load Spectra (ALS) concept as recommended by the MEPDG seems to be a logical approach, the integration of which with monthly or seasonal environmental factors such as humidity and temperature differentials often resulted in more variations in the predictions of joint faulting due to many uncertainties involved. The prediction accuracy of the existing faulting models for jointed concrete pavements using the Long-Term Pavement Performance (LTPP) database was found to be inadequate and greatly in need for improvements. A relatively skewed distribution for actual joint faulting was identified, which also indicated that normality assumption using conventional regression techniques might not be appropriate for this study. Thus, generalized linear model (GLM) and generalized additive model (GAM) were adopted for the modeling process. After many trails in eliminating insignificant and inappropriate parameters, the resulting mechanistic-empirical model included several variables such as pavement age, yearly ESALs, bearing stress, annual precipitation, base type, subgrade type, annual temperature range, joint spacing, modulus of subgrade reaction, and freeze-thaw cycle for the prediction of joint faulting. The goodness of the model fit was further examined. The plot of the response versus fitted values indicated that the proposed dowelled faulting model has substantial improvements over the existing models. However, the goodness of prediction of the nondowelled faulting model still contains large variability. 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.

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