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Development of Transverse Cracking Prediction Models for Jointed Concrete Pavements Using LTPP Database

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Abstract: The main objective of this study is to develop improved transverse cracking 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 indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for this study. Therefore, several modern regression techniques including generalized linear model (GLM) and generalized additive model (GAM) along with the assumption of Poisson distribution were adopted for the modeling process. The resulting mechanistic-empirical model included several variables such as pavement age, yearly ESALs, accumulated ESALs, annual precipitation, freeze-thaw cycle, annual temperature range, stress ratio, and percent steel for the prediction of transverse cracking. 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.

INTRODUCTION

Performance predictive models have been used in various pavement design, evaluation, rehabilitation, and network management activities. Transverse cracking 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 transverse cracking to accumulated traffic, fatigue damage, environmental effects, and several other design parameters (1, 2, 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 transverse cracking prediction models for jointed concrete pavements using the Long-Term Pavement Performance (LTPP) database (<http://www.datapave.com> or LTPP DataPave Online) (5-7).

BRIEF 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. The following models were developed for the prediction of transverse cracking:

$$\begin{aligned}
 CRACKSJP = & ESAL^{2.755} * [3092.4 * (1 - SOILCRS) * RATIO^{10}] + ESAL^{0.5} * \\
 & (1.233 * TRANGE^2 * RATIO^{2.868}) + ESAL^{2.416} * (0.2296 * FI^{1.53} \\
 & * RATIO^{7.31})
 \end{aligned} \tag{1}$$

Statistics : $R^2 = 0.69$, SEE = 176, N = 303

$$\begin{aligned}
 CRACKSJR = & ESAL^{0.897} * [7130 * JTSPACE / (ASTEEL * THICK^5)] \\
 & + ESAL^{0.1} * (2.281 * PUMP^5) + ESAL^{2.16} [1.81 / (BASETYP + 1)] \\
 & + AGE^{1.3} * [0.0036 * (FI + 1)^{0.36}]
 \end{aligned} \tag{2}$$

Stastics : $R^2 = 0.41$, SEE = 280, N = 314

In which, CRACKSJP is the total length of transverse cracking including low, medium, and high severities (ft/mile), ESAL is the accumulated 18-kip ESALs (millions), SOILCRS is the subgrade classification (1 for A1-A3 coarse-grained soil, 0 for A4-A7 fine-grained soil), TRANGE is the yearly temperature tange ($^{\circ}$ F), RATIO is the stress ratio defined as the ratio of Westergaard edge stress versus concrete modulus of rupture, FI is the freeze index ($^{\circ}$ F-days). CRACKSJR is the sum of medium and high severity transverse cracking (ft/mile), JTSPACE is the mean transverse joint spacing (ft), ASTEEL is the cross area of reinforcing steels (in^2/ft width), THICK is the slab thickness (in), PUMP represents the pumping status (0 for no pumping, 1, 2, and 3 for low, medium, and high severity pumping, respectively), BASETYP represents base types (0 for granular base, 1 for treated base), and AGE is the pavement age (years). R^2 is the coefficient of determination, SEE is the standard error of estimates, and N is the number of observations.

For the calculation of Westergaard edge stress, a single wheel load of 9,000 lbs (40kN), a concrete modulus of elasticity of 4.2 Mpsi (28.9 GPa), a Poisson's ratio of 0.2, and a load radius of 6.4 in. (16.36 cm) were used. For JPCP model, the increase of slab thickness will result in stress reduction and thus significantly reduce the occurrence of transverse cracking. Sensitivity analysis also indicates that if the concrete modulus of rupture is below 600 psi (4.13 MPa) the stress ratio becomes higher which will result in more transverse cracking. 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 transverse cracking.

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 NCHRP project P-393 (2), an early sensitivity analysis study of the LTPP

database was conducted and the following models were developed for the prediction of transverse cracking:

$$PCRACKED = \frac{1}{0.01 + 10 * 100^{-\log_{10} FD}}$$

$$FD = \sum_{i=1}^k (n_i / N_{fi}) \quad (3)$$

$$N_f = 10^{[2.13 * (1 / RATIO)^{1.2}]}$$

$$CRACKSJR = -72.9 + 1.9 * ESAL + 0.182 \left(\frac{1}{PSTEEL^2} \right) +$$

$$2473 * \left(\frac{1}{KSTATIC} \right) + 0.697 * PRECIP \quad (4)$$

Statistics : $R^2 = 0.48$, $SEE = 20.8$, $N = 27$

In which, PCRACKED is the percent of slabs with transverse cracking for JPCP pavements (%), FD is the estimated cumulative fatigue damage, k is the number of axle load type, n_i is the expected number of load repetitions under different axle load types, and N_{fi} is the corresponding maximum allowable number of repetitions. CRACKSJR is the number of medium and high severity transverse cracking (no./mile), PSTEEL is the percent of longitudinal reinforcing steel (%), PRECIP is the average annual precipitations (in), KSTATIC is the modulus of subgrade reaction (psi/in).

Westergaard edge stress and curling stress equations (8) were used to account for the combination effects of loading and thermal curling. Table 1 shows the recommended temperature gradients in different climatic zones and slab thicknesses. A single wheel load of 9,000 lbs (40 kN) and a slab thermal expansion coefficient of $5.5 * 10^{-6}$ (1/°F) were used in the analysis. Cumulative fatigue damage is determined by adding the damage caused by each individual load application based on Miner's hypothesis accordingly. Slab thickness and the modulus of rupture are important factors affecting the calculating of fatigue damage and the estimating of transverse cracking. Sensitivity analysis also indicated that lower modulus of subgrade reaction or lower percentage of reinforcing steel will result in higher deflection, larger crack width, and thus more transverse cracking for JRCP pavements. Similar conclusions may be achieved for pavements with higher traffic and precipitations as well.

In the recommended MEPDG (4), both bottom-up and top-down cracking are considered for the prediction of JPCP transverse cracking. No prediction model was proposed for JRCP pavements. The fatigue cracking damage for JPCP is determined in an incremental manner based on more complicated Axle Load Spectra (ALS) concept. Various artificial neural networks models were developed based on the ISLAB2000 finite element model to compute critical stresses and deflections. Monthly damage 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 differences. 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 difference. The proposed model is briefly summarized as follows:

TABLE 1 Assumed Temperature Gradients in Different Climatic Zones (2)

Climatic Zones	Slab Thickness (in)	Assumed Temperature Gradient (°F/in)
Non-Freeze	8	1.4
	9	1.3
	10	1.21
	11	1.11
	12	1.01
Freeze	8	1.13
	9	1.05
	10	0.96
	11	0.87
	12	0.79

$$PCRAKED = \frac{1}{1 + FD^{-1.68}}$$

$$FD = \sum \frac{n_{i,j,k,l,m,n}}{N_{i,j,k,l,m,n}} \quad (5)$$

Statistics : $R^2 = 0.75$, $SEE = 6.9$, $N = 516$

In which, $n_{i,j,k,l,m,n}$ is the applied number of axle loads under each condition: i is for age to account for change in modulus of rupture, layer bond condition, and deterioration of shoulder load transfer efficiency. j represents month to account for change in base and effective dynamic modulus of subgrade reaction. k is for axle type (single, tandem, and tridem for bottom-up cracking; short, medium, and long wheelbase for top-down cracking). l represents load level for each axle type, m is for temperature difference, n is for traffic path. $N_{i,j,k,l,m,n}$ is the corresponding allowable number of load applications determined by the following field calibrated fatigue mode. MR_i is the PCC modulus of rupture (psi) at age i and $\sigma_{i,j,k,l,m,n}$ is the estimated stress (psi) at each condition.

$$\log(N_{i,j,k,l,m,n}) = 2.0 * \left(\frac{MR_i}{\sigma_{i,j,k,l,m,n}} \right)^{1.22} + 0.4371 \quad (6)$$

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, Standard 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. The database is implemented in an information management system (IMS) which is a relational database structure using ORACLE program. However, the standard releases are in Microsoft Access database structure. 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 modulus of rupture, plasticity index, percent passing no. 4 sieve, etc. 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.

Since there are distinct differences in the distress data collected from two methods of distress data collection, i.e., both manual survey (MON_DIS_JPCC_REV) and photographic survey (MON_DIS_PADIAS42_JPCC) (9). Although techniques in collecting and interpreting LTPP photographic distress data may have been improved (10), only manual survey data is used in this study for simplicity and consistency reasons. The transverse cracking data (low, medium, and high severities for JPCP and medium and high severities for JRCP) was obtained from MON_DIS_JPCC_REV 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 (11) 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.

A data cleaning process must be conducted before any preliminary analysis or regression analysis can be performed. With the help of graphical representation, transverse cracking data were plotted against surveyed years for each section in the database with additional information displayed. For example, a plot as shown in Figure 1 was used to examine the distress trends in order to identify possible data errors. The state code, SHRP identification number, modulus of rupture (MPa), slab thickness (cm), 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 transverse cracking 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 6/3005 with the remaining data, it was found that this section probably had some maintenance or rehabilitation 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.

COMPARISON OF LABORATORY TESTED AND BACKCALCULATED MODULI

The modulus of each pavement layer backcalculated using the ERESBACK 2.2 program (12) 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. Figure 2(a)-(c) depicts the average ratios are approximately 1.4, 1.5, and 1.5 for surface, subbase, and subgrade layers for dense liquid foundation, respectively. Note that very few laboratory tested modulus of subgrade reaction are available in the database. Likewise, Figure 2(d)-(f) depicts the average ratios are roughly 1.0, 1.1, and 3.0 for surface, subbase, and subgrade layers for elastic solid foundation, respectively (7). For consistency reasons, the recommendation of dividing the backcalculated modulus of subgrade reaction (or k-value) by 2 as the static k-value by AASHTO (13) was used in the calculation of stress ratio in this study.

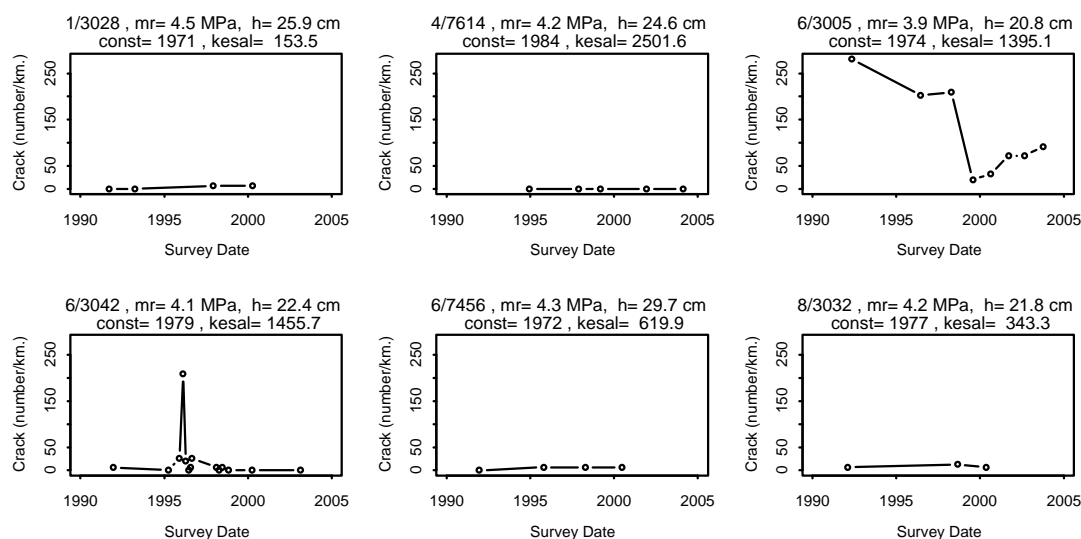


FIGURE 1 Some transverse cracking history of JPCP pavements.

RELATIONSHIP BETWEEN ELASTIC MODULUS AND MODULUS OF SUBGRADE REACTION

For practical concerns, a relationship between the elastic modulus and the modulus of subgrade reaction is often needed. According to the literature (12), the following empirical relationship was developed from the GPS and SPS data analysis:

$$k = 0.296E_s \quad (7)$$

Statistics : $R^2 = 0.872$, $SEE = 9.37$, $N = 596$

In which, k is the modulus of subgrade reaction (MPa/m) and E_s is the subgrade elastic modulus (MPa). According the available GPS data, very good agreements have been achieved using the above relationship.

Nevertheless, Barenberg (14) have indicated the theoretical difference using elastic solid foundation or dense liquid foundation for having same maximum deflections in backcalculation analysis. Assuming a Poisson ratio of 0.5 for subgrade, a Poisson ratio of 0.15 for concrete slab, and the elastic modulus of the slab is 4 Mpsi (27.6 GPa), the following relationship was derived after some simplification process.

$$E_s^{4/3} = 283.7 * h * k \quad (8)$$

In which, k is the modulus of subgrade reaction (pci), E_s is the subgrade elastic modulus (psi), and h is the slab thickness (in). As shown in Figure 3(a), the effect of slab thickness has to be considered in such a relationship.

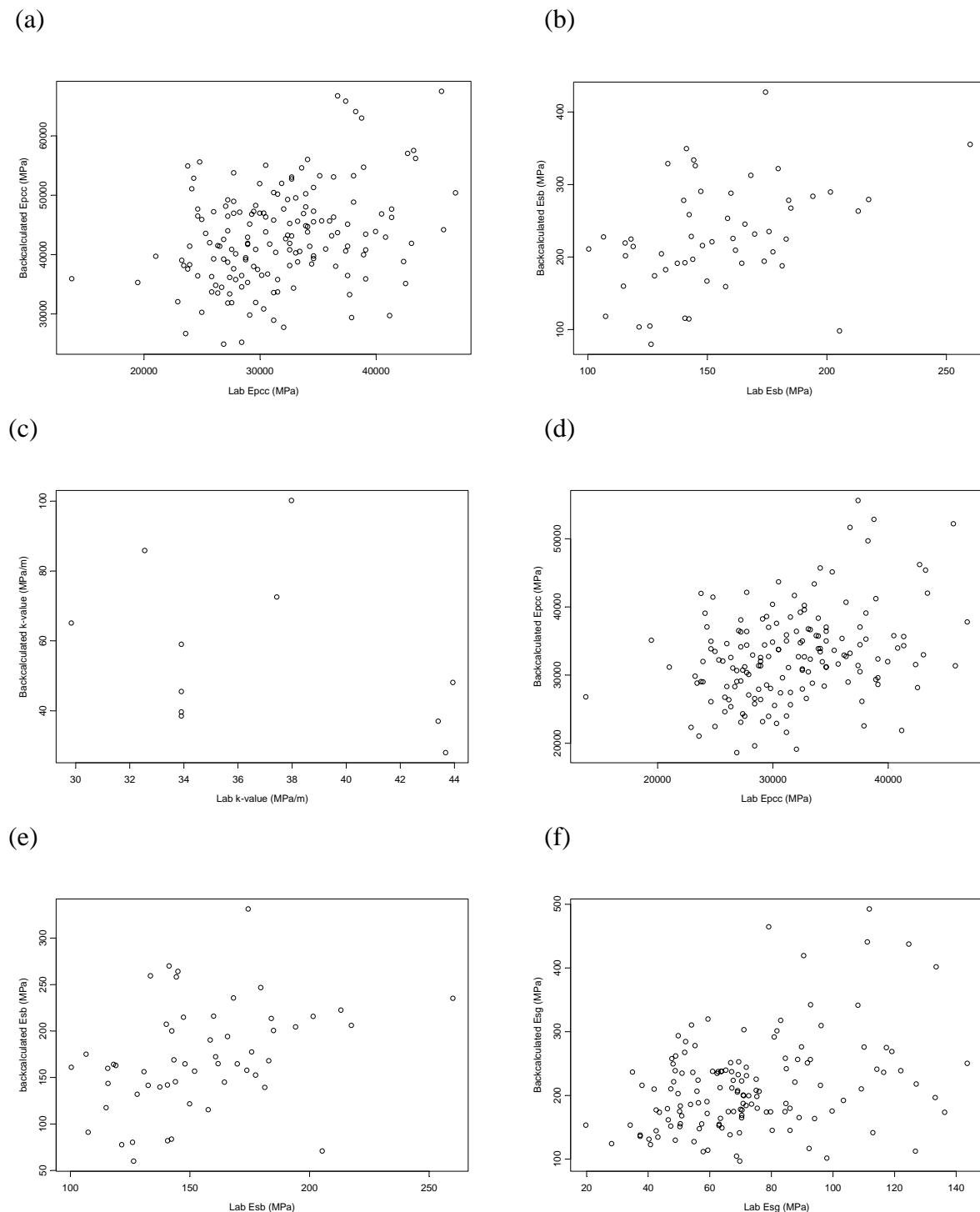


FIGURE 2 Comparison of laboratory tested and backcalculated layer moduli of (a) surface, (b) subbase, and (c) subgrade for dense liquid foundation; and (d), (e), (f) for elastic solid foundation, respectively.

The aforementioned relationship was further verified by comparing the backcalculated subgrade elastic moduli with the backcalculated modulus of subgrade reaction from the LTPP database. Slab thickness did have significant effects on this relationship as shown in Figure 3(b). Consequently, the following relationship is developed using regression techniques. In which, k is the modulus of subgrade reaction (MPa/m), E_s is the subgrade elastic modulus (MPa), and h is the slab thickness (cm).

$$E_s = 0.9015(k * h)^{3/4} \quad (9)$$

Statistics : $R^2 = 0.9524$, $SEE = 15.87$, $N = 138$

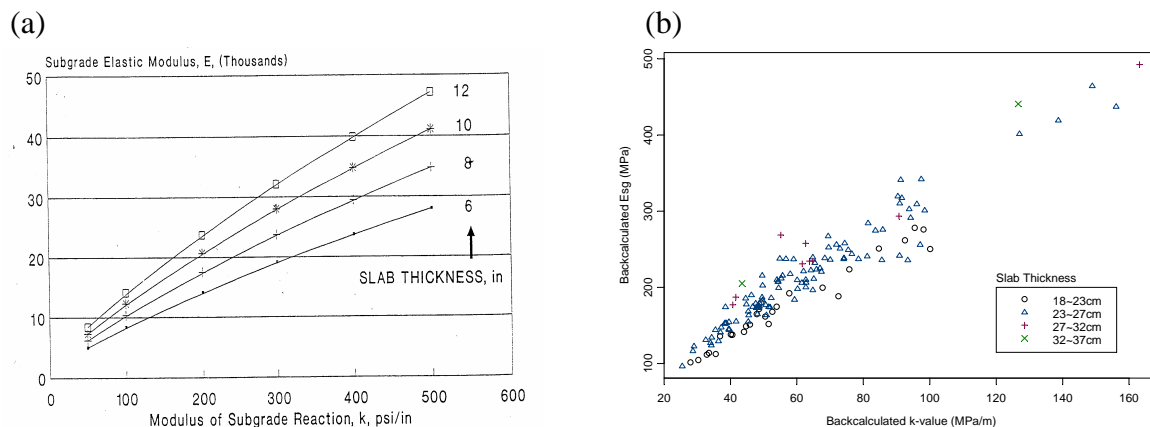


FIGURE 3 Comparison of elastic solid foundation versus dense liquid foundation: (a) theoretical comparison (14); (b) backcalculated results.

PRELIMINARY ANALYSIS OF THE FATIGUE CRACKING 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 JPCP pavements regarding the data range, its variation, and the number of observations for each individual variable are given in Table 2. 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. In which, age stands for pavement age (years); kesalpyr is the yearly ESALs (thousands); cesal is the cumulative ESALs (millions); jtspc is the transverse joint spacing (m); hpcc is the slab thickness (cm); fi is yearly freezing index ($^{\circ}\text{C}$ -days); precip is mean annual precipitation (mm); kstatic is the modulus of subgrade reaction (MPa/m); trange is the difference of maximum and minimum mean annual temperature ($^{\circ}\text{C}$); days32 is the number of days temperature above 32°C ; ft is yearly freeze-thaw cycle; mr is the concrete modulus of rupture (MPa); ratio is stress ratio; act.crack is the percent of cracked slabs (%).

A graph is always 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 skewness as well. A histogram only displays a rough and crude shape of the distribution of data. To have a smoother look, a continuous curve of the nonparametric estimate of the probability density may also be obtained. A normal

probability plot or a quantile-quantile plot can be used to have a quick visual check on the assumption of normal distribution. If the distribution is close to normal, the plot will show approximately a straight-line relationship. The distribution of transverse cracking (act.crack) of JPCP pavements is shown in Figure 4. The solid horizontal line in the box plot indicates the median of the data whereas the upper and lower ends of the box show the upper and lower quantiles, respectively. These plots reveal a relatively skewed distribution for actual transverse cracking.

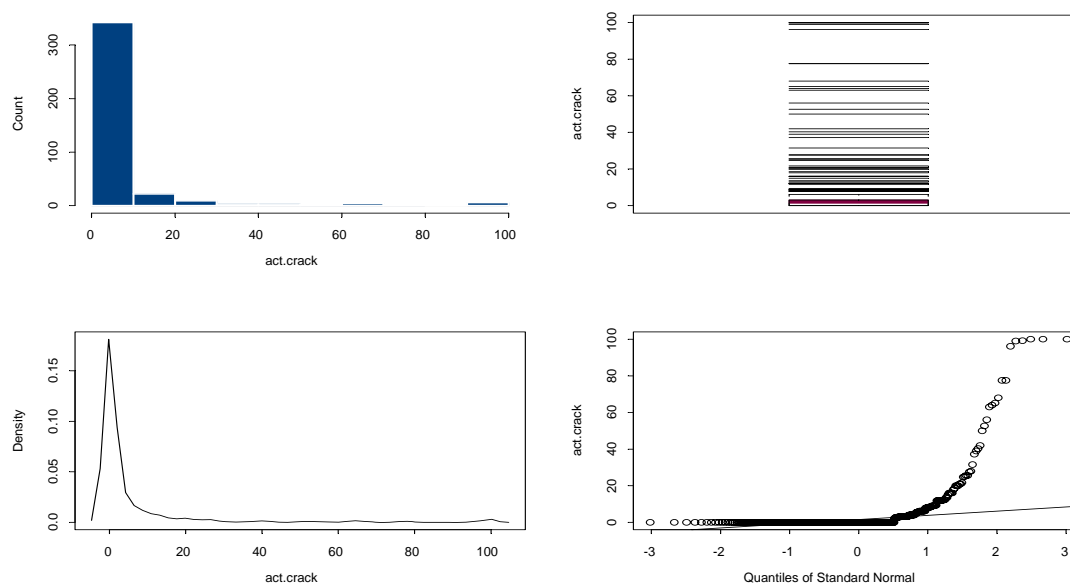


FIGURE 4 Exploratory data analysis: transverse cracking of JPCP pavements.

Bivariate and Multivariate Analysis

A correlation matrix of these variables is also given in Table 2. 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 Figure 5 become clearer and possible data errors may also be identified. In which, age, cesal, trange, and ft have better correlations with actual transverse cracking (act.crack), although very high variations are still observable. The slab thickness (hpcc) is highly correlated with stress ratio (ratio) and transverse joint spacing (jtospace) is also highly correlated with annual precipitation (precip). Special cautions are needed during the modeling process to avoid potential collinearity problems.

INVESTIGATION OF THE GOODNESS OF FIT OF THE EXISTING MODELS

To investigate the goodness of predictions, the aforementioned predictive models given in equations (1) to (4) were used to predict the occurrence of transverse cracking and the results were plotted against the actual observed data. Figure 6(a)-(b) shows the goodness of prediction using NCHRP 1-19 models for JPCP and JRCP pavements, respectively. Similarly, Figure 6(c)-(d) depicts the results of this comparison using P-393 models for JPCP and JRCP

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, it was found that the circled data with relatively high predictions in Figure 6(d) was because of the very small longitudinal reinforcement.

TABLE 2 Univariate Statistics and Multiple Correlations of JPCP Pavements

(a) Univariate Statistics:												
	N	MEAN	STD DEV	SUM	MIN	MAX						
age	393	16.44	6.34	6460.90	2.34	35.64						
kesalpyr	393	485.72	433.73	190886.02	20.21	2501.62						
cesal	393	7.83	7.45	3077.23	0.16	33.90						
jtspace	393	5.02	0.83	1972.18	3.51	6.55						
hpcc	393	24.22	2.97	9518.14	16.26	36.32						
fi	393	246.92	367.12	97039.23	0.00	1777.22						
precip	393	883.58	428.66	347248.12	118.71	1725.67						
kstatic	393	33.80	14.79	13281.69	12.75	81.58						
trange	393	12.87	2.08	5058.77	8.40	18.04						
days32	393	43.88	31.41	17245.62	0.15	174.35						
ft	393	68.31	44.00	26846.65	0.00	173.13						
mr	393	4.46	0.41	1754.72	3.03	5.88						
ratio	393	0.44	0.10	173.40	0.21	0.77						
act.crack	393	5.71	16.22	2242.50	0.00	100.00						

(b) Correlation Matrix:												
	age	cesal	jtspace	hpcc	fi	precip	kstatic	trange	ft	mr	ratio	act.crack
age	1.00	0.26	0.16	-0.13	-0.10	0.13	-0.18	-0.17	-0.11	-0.14	0.17	0.16
cesal	0.26	1.00	0.02	0.17	-0.27	-0.17	0.06	0.37	-0.13	-0.12	-0.20	0.33
jtspace	0.16	0.02	1.00	0.02	-0.18	0.68	0.20	-0.21	-0.18	-0.10	-0.09	0.01
hpcc	-0.13	0.17	0.02	1.00	-0.07	-0.01	0.16	0.01	0.00	0.00	-0.86	-0.02
fi	-0.10	-0.27	-0.18	-0.07	1.00	-0.27	-0.24	-0.16	0.46	-0.07	0.21	-0.06
precip	0.13	-0.17	0.68	-0.01	-0.27	1.00	0.20	-0.58	-0.40	0.01	-0.02	-0.02
kstatic	-0.18	0.06	0.20	0.16	-0.24	0.20	1.00	0.02	-0.13	0.09	-0.37	0.03
trange	-0.17	0.37	-0.21	0.01	-0.16	-0.58	0.02	1.00	0.36	0.02	-0.10	0.20
ft	-0.11	-0.13	-0.18	0.00	0.46	-0.40	-0.13	0.36	1.00	0.04	0.00	0.19
mr	-0.14	-0.12	-0.10	0.00	-0.07	0.01	0.09	0.02	0.04	1.00	-0.38	-0.03
ratio	0.17	-0.20	-0.09	-0.86	0.21	-0.02	-0.37	-0.10	0.00	-0.38	1.00	0.00
act.crack	0.16	0.33	0.01	-0.02	-0.06	-0.02	0.03	0.20	0.19	-0.03	0.00	1.00

(c) Trimmed Correlation Matrix (Deleted 3 Percent of the Data):												
	age	cesal	jtspace	hpcc	fi	precip	kstatic	trange	ft	mr	ratio	act.crack
age	1.00	0.30	0.20	-0.11	0.05	0.16	-0.18	-0.17	-0.13	-0.16	0.19	0.18
cesal	0.30	1.00	0.04	0.26	-0.15	-0.18	0.11	0.43	-0.14	-0.08	-0.25	0.30
jtspace	0.20	0.04	1.00	0.05	-0.14	0.71	0.22	-0.19	-0.16	-0.16	-0.09	0.02
hpcc	-0.11	0.26	0.05	1.00	-0.04	-0.05	0.21	0.10	0.04	0.09	-0.88	0.08
fi	0.05	-0.15	-0.14	-0.04	1.00	-0.27	-0.15	-0.13	0.60	0.10	0.15	0.18
precip	0.16	-0.18	0.71	-0.05	-0.27	1.00	0.18	-0.60	-0.42	-0.13	0.05	-0.08
kstatic	-0.18	0.11	0.22	0.21	-0.15	0.18	1.00	0.11	-0.10	0.17	-0.38	0.14
trange	-0.17	0.43	-0.19	0.10	-0.13	-0.60	0.11	1.00	0.39	0.06	-0.15	0.17
ft	-0.13	-0.14	-0.16	0.04	0.60	-0.42	-0.10	0.39	1.00	0.17	-0.05	0.16
mr	-0.16	-0.08	-0.16	0.09	0.10	-0.13	0.17	0.06	0.17	1.00	-0.38	0.19
ratio	0.19	-0.25	-0.09	-0.88	0.15	0.05	-0.38	-0.15	-0.05	-0.38	1.00	-0.03
act.crack	0.18	0.30	0.02	0.08	0.18	-0.08	0.14	0.17	0.16	0.19	-0.03	1.00

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 cracking. The beta version of the software could be downloaded from <http://www.trb.org/mepdg/software.htm>. A total of 22 JPCP pavement sections containing 102 data points were randomly selected for this analysis. The goodness of transverse cracking prediction using NCHRP Project P-393 models as well as the recommended MEPDG models is shown in Figure 6(e)-(f). Apparently, the prediction accuracy of the existing prediction models was found to be inadequate.

DEVELOPMENT OF IMPROVED TRANSVERSE CRACKING MODELS

The occurrence of transverse cracking in field depends on various factors namely traffic, environment, structure, construction, maintenance and rehabilitation. Even though the use of cumulative fatigue damage based on Miner's hypothesis 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 such as humidity and temperature differentials often resulted in more variations in the predictions of transverse cracking as shown in Figure 6(c), (e), and (f) due to many uncertainties involved.

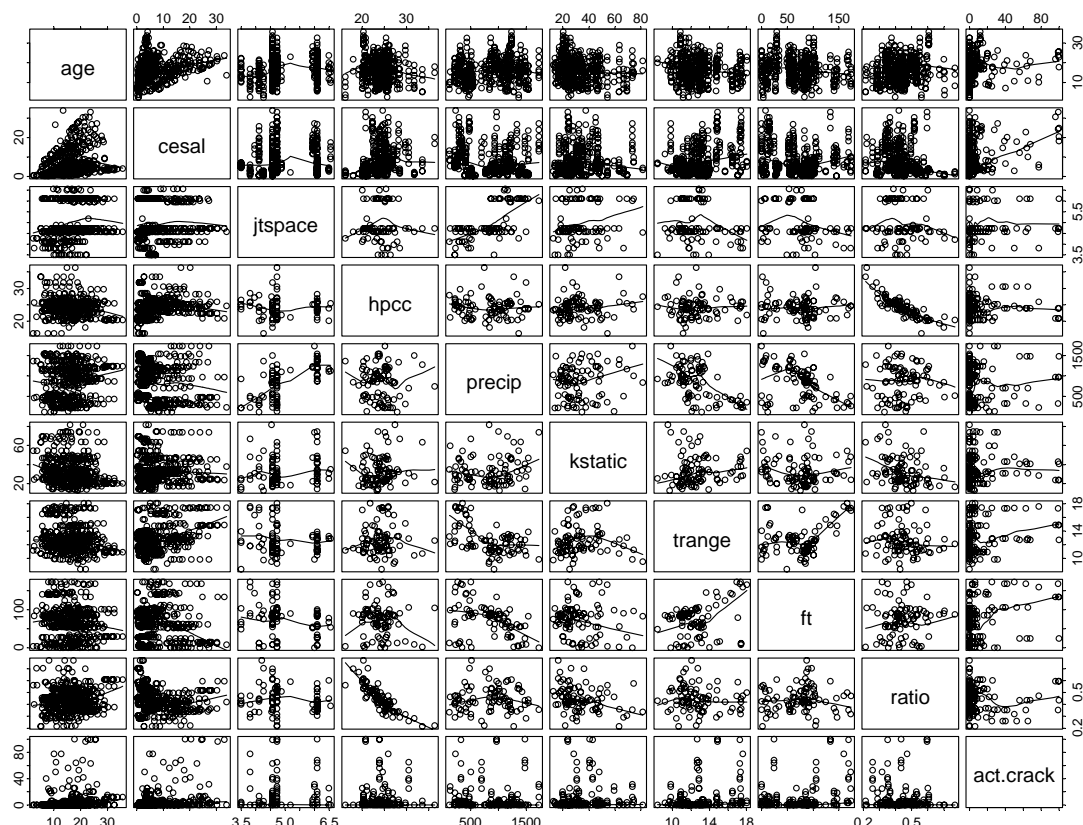


FIGURE 5 Using scatter plot smoother (lowess) on the scatter plot matrix for JPCP pavements.

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 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 easily utilized for model development. Nevertheless, many preliminary trials using these regression techniques have shown extreme difficulty to achieve a satisfactory predictive model for this set of data.

Exploratory data analysis of the response variable as shown in Figure 4 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 transverse cracking was tested for departures from normality using Shapiro and Wilk's W-statistic (11). Various transformations including logarithm of the transverse cracking were tested, although the W-statistic still indicated that transverse cracking is not lognormal distributed either. Due to the data collecting nature of transverse cracking, it could be treated as rate data, i.e., percent of cracked slab. Agresti suggested that "when events of a certain type occur over time, space, or some other index of size, it is often relevant to model the rate at which events occur," and using Poisson regression for rate data is an appropriate decision (17).

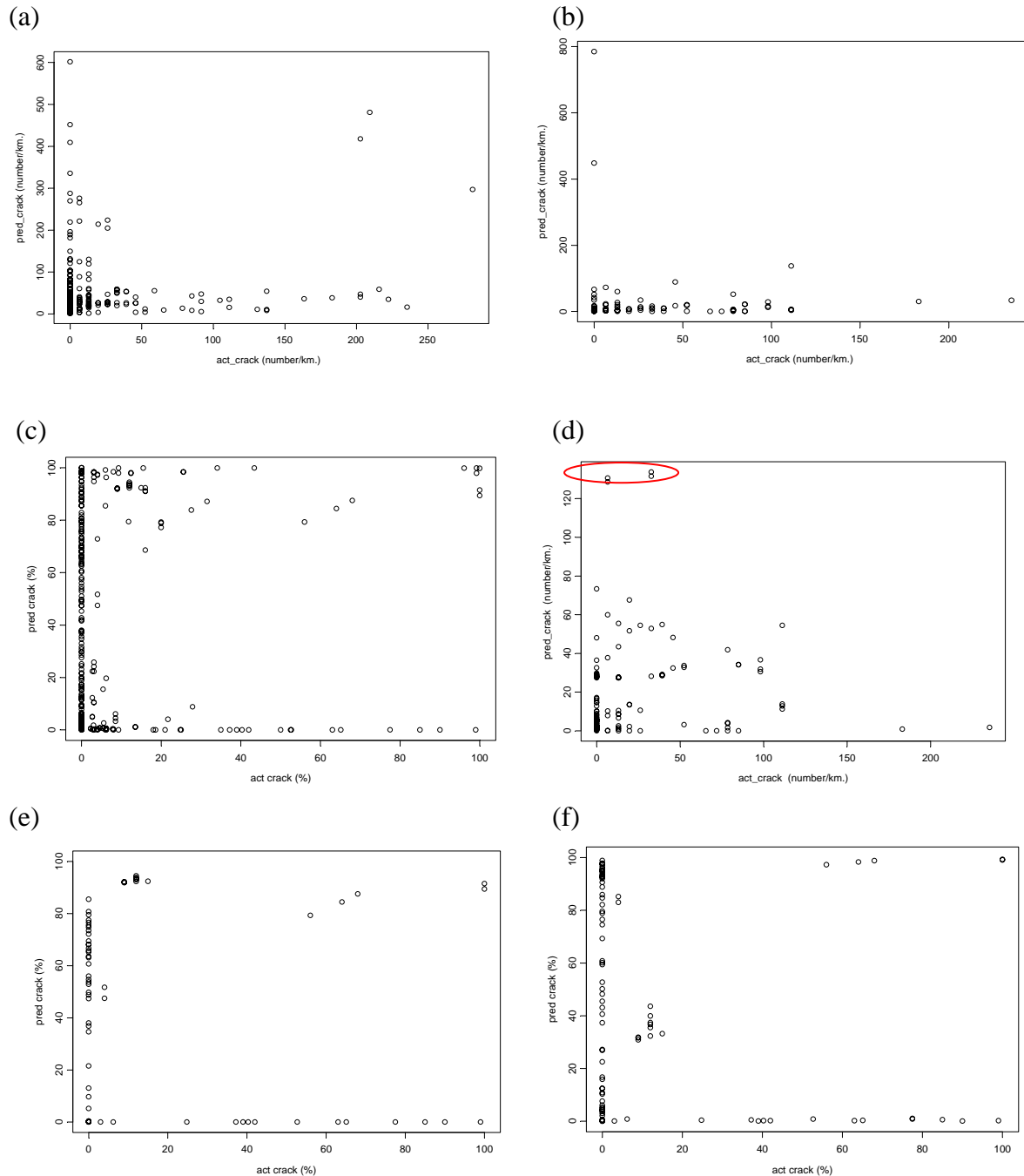


FIGURE 6 Comparison of prediction results using (a) NCHRP 1-19 JPCP; (b) NCHRP 1-19 JRCP; (c) P-393 JPCP; (d) P-393 JRCP; (e) P-393 JPCP; and (f) DG2002 models.

Preliminary Analysis Using Poisson Regression Techniques

Therefore, generalized linear model (GLM) (18) along with the assumption of Poisson distribution was adopted in this analysis. In which, a Poisson loglinear model is a GLM that assumes a Poisson distribution for the response variable and uses the log link. Many factors including age, kesalpyr, cesal, jtSPACE, hpcc, fi, precip, kstatic, trange, days32, ft, basetype, stype, edgestress, mr, ratio, and psteel were considered in the beginning trial analysis. In which, basetype represents base types (0 for granular base, 1 for treated base); stype represents subgrade types (1 for A1-A3 coarse-grained soil, 0 for A4-A7 fine-grained soil); edgestress is the estimated Westergaard edge stress (MPa); and the remaining variables are as previously defined. After going through several trails in eliminating insignificant and/or inappropriate parameters from both statistical and engineering viewpoints, the following models were obtained:

$$\ln(PCRACKED) = -6.105 + 0.1015 * age + 0.001317 * kesalpyr \\ + 0.001209 * precip + 0.01284 * ft + 0.1999 * trange + 1.031 * ratio \quad (10)$$

Statistics : N = 393, Null Deviance = 8138.5, Residual Deviance = 5402.1

$$\ln(CRACKSJR) = -0.9396 + 0.06729 * cesal + 0.02152 * ft + 0.2326 * trange \\ - 10.26 * psteel \quad (11)$$

Statistics : N = 151, Null Deviance = 5391.9, Residual Deviance = 2991.3

In which, PCRACKED is the percent of cracked slabs for JPCP pavements (%); CRACKSJR is the number of medium and high severity transverse cracking (no./km). The dispersion parameter for Poisson family was taken to be 1. Of which, a total of 74, 43, 114, and 162 data points were obtained from Dry-Freeze, Dry-NonFreeze, Wet-Freeze, and Wet-NonFreeze zones for JPCP pavements, whereas the performance data of JRCP pavements consist of only 80 and 71 observations from Wet-Freeze and Wet-NonFreeze zones, respectively.

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 (19). 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 transverse cracking data was refitted with these transformed predictors using generalized linear model (GLM) techniques. Visual graphical techniques as well as the systematic statistical and engineering approach proposed by Lee and Darter (15, 16) were frequently adopted during the prediction modeling process. A plot of residuals versus the fitted values can be used to check the adequacy of the model. If any curvature is observed, then the model might be improved by adding additional, nonlinear terms to the model.

After considerable amount of trails, the following models were separately developed for the transverse cracking prediction of JPCP and JRCP pavements. As shown in Figure 7, a plot of the observed versus the fitted values is provided to illustrate the goodness of the fit.

$$PCRACKED = \exp[-9.913 + 3.711 * \log(\text{age}) + 1.931 * \log \text{kesalpyr} + 0.05116 * \sqrt{\text{precip}} + 0.01186 * \text{ft} - 26.71 * \frac{1}{\text{trange}} + 2.496 * \sqrt{\text{ratio}}] \quad (12)$$

Statistics : N = 393, R² = 0.358, SEE = 13.01

$$CRACKSJR = \exp[5.863 - 1.780 * \frac{1}{\sqrt{\text{cesal}}} + 0.2397 * \sqrt{FT} - 37.25 * \frac{1}{\text{trange}} - 10.12 * \text{psteel}] \quad (13)$$

Statistics : N = 151, R² = 0.380, SEE = 20.79

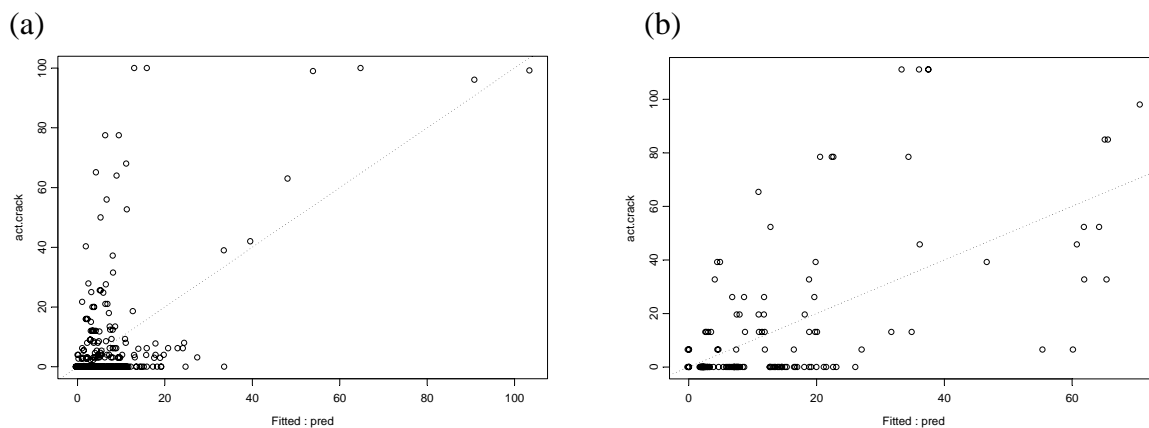


FIGURE 7 Goodness of fit of the proposed model for: (a) JPCP and (b) JRCP pavements.

To further 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. For example, the following two models could be subsequently developed using the same functional forms with somewhat better regression statistics for JPCP pavements in Wet-NonFreeze zone and JRCP pavements in Wet-Freeze zone, respectively. Nevertheless, it is still possible to develop better and more refined models with more efforts in identifying other important factors and functional forms under different climatic conditions.

$$(PCRACKED)_{WNF} = \exp[-37.33 + 7.042 * \log(\text{age}) + 4.565 * \log \text{kesalpyr} + 0.2242 * \sqrt{\text{precip}} - 0.02321 * \text{ft} - 71.77 * \frac{1}{\text{trange}} + 24.77 * \sqrt{\text{ratio}}] \quad (14)$$

Statistics : N = 162, R² = 0.818, SEE = 8.26

$$(CRACKSJR)_{WF} = \exp[7.142 - 1.927 * \frac{1}{\sqrt{\text{cesal}}} + 0.1459 * \sqrt{FT} - 41.87 * \frac{1}{\text{trange}} - 8.500 * \text{psteel}] \quad (15)$$

Statistics : N = 80, R² = 0.393, SEE = 23.95

Sensitivity Analysis of the Tentatively Proposed Models

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 tentatively proposed models, i.e., equations (12) and (13), are presented in Figure 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 annual temperature range (trange), yearly ESALs (kesalpyr), stress ratio (ratio), pavement age (age) for the JPCP model, and yearly freeze-thaw cycle (ft), cumulated ESAL (cesal), and percent of reinforcing steel (psteel) for the JRCP model. The general trends of these effects seem to be fairly reasonable.

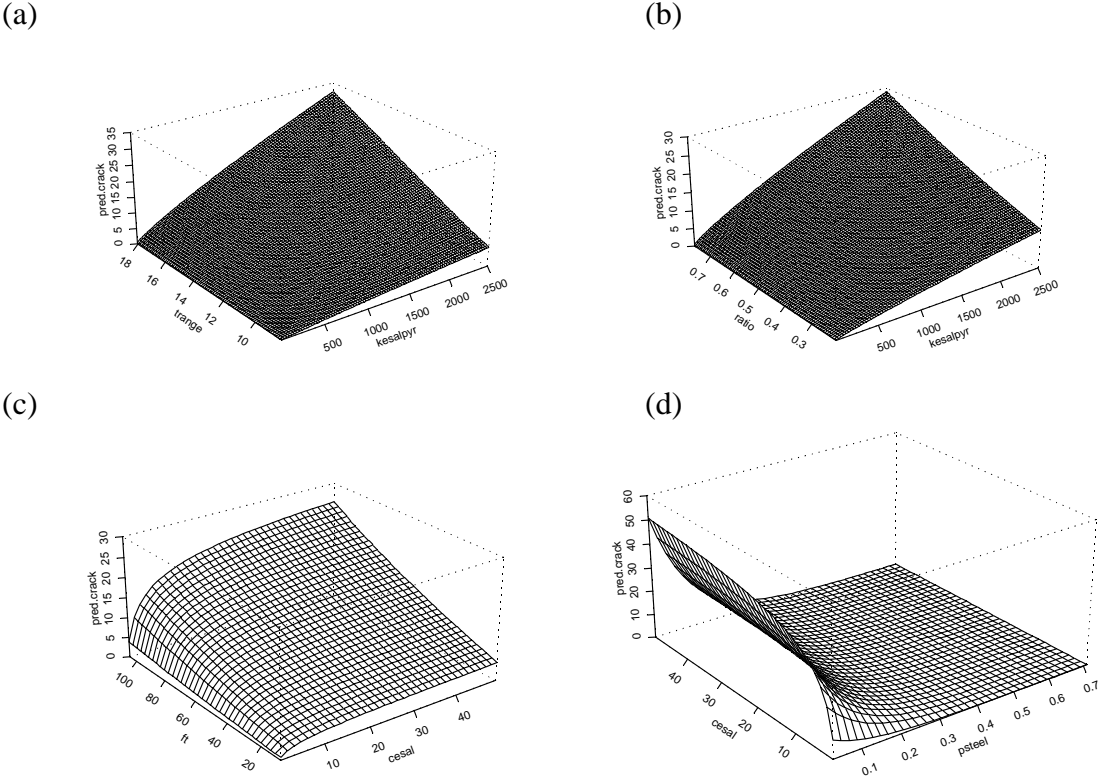


FIGURE 8 Sensitivity analysis of the proposed model for: (a)-(b) JPCP; and (c)-(d) JRCP.

DISCUSSIONS AND CONCLUSIONS

Even though the use of cumulative fatigue damage based on Miner’s hypothesis and more complicated Axle Load Spectra (ALS) concept as recommended by the MEPDG seems to be a very 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 transverse cracking due to many uncertainties involved. The prediction accuracy of the existing transverse cracking models for jointed concrete pavements was found to be inadequate and greatly in need for improvements.

A relatively skewed distribution for actual transverse cracking 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) along with the assumption of Poisson distribution were adopted for the modeling process. After many trials in eliminating insignificant and inappropriate parameters, the resulting proposed models included several variables such as pavement age, yearly ESALs,

1 cumulated ESALs, annual precipitation, freeze-thaw cycle, annual temperature range, stress
2 ratio, and percent steel for the prediction of transverse cracking.

3 The goodness of the model fit was further examined. The plot of the response versus
4 fitted values indicated that the proposed model has substantial improvements over the existing
5 models. Sensitivity analysis of the explanatory variables indicated their general trends seem to
6 be fairly reasonable. The tentatively proposed predictive models appeared to reasonably agree
7 with the pavement performance data although their further enhancements are possible and
8 recommended.

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