6th ICPT2008

The 6th International Conference on Road and Airfield Pavement Technology

20-23 July, 2008

Sappore Convention Center, Sapporo, JAPAN

The Committee on Pavement Engineering, JSCE

The 6th International Conference on Road and Airfield Pavement Technology

Proceedings

20-23, July, 2008
Sapporo Convention Center, Sapporo, JAPAN

Editor in Chief
Yoshitaka Hachiya

Organized by
The Committee on Pavement Engineering
Japan Society of Civil Engineers

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DEVELOPMENT OF ROUGHNESS PREDICTION MODELS FOR RIGID PAVEMENTS USING LTPP DATABASE

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ABSTRACT
This study strives to develop improved roughness prediction models for rigid pavements using the Long-Term Pavement Performance (LTPP) database. Without assuming the error distribution of the response variable, generalized linear model (GLM) and general additive model (GAM) were adopted in this study. Box-Cox power transformation technique, visual graphical techniques, and a systematic statistical and engineering approach were adopted during the 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 goodness of the fit was further examined through significant testing and sensitivity analyses of pertinent explanatory parameters. The tentatively proposed predictive models appeared to reasonably agree with the pavement performance data.

KEY WORDS
rigid pavement, roughness, performance, prediction model, LTPP

INTRODUCTION

Roughness has been recognized as one of major performance measures primarily caused by accumulated traffic loads and environmental effects. Extensive research has been conducted to predict the amount of this distress type in terms of International Roughness Index (IRI) [1] using various empirical and mechanistic-empirical approaches. Conventional predictive models usually correlate IRI to accumulated traffic, joint types, environmental effects, and several other design parameters[2]. 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)[3]. The success of the new 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 roughness prediction models for rigid pavements using the Long-Term Pavement Performance (LTPP) database[4].

REVIEW OF EXISTING MECHANISTIC-EMPIRICAL PREDICTION MODELS

The NCHRP Project 1-19 was conducted with the primary objective of developing a system for statewide and nationwide evaluation of concrete pavement performance[5]. 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. Eight additional JRCP pavement sections from Nebraska were also included in this database. Several combinations of multiple regression, stepwise regression, and nonlinear regression techniques were used to develop various distress and serviceability prediction models using SPSS statistical package.

Since 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[6], the LTPP program has been collecting a national pavement database in a factorial format with wider ranges of pavement designs, materials, and climatic zones starting from 1987. More than 2,400 asphalt and Portland cement concrete pavement test sections across the North America have been monitored. In the NCHRP project P-393, an early sensitivity analysis study of the LTPP database was conducted and models as shown in Table 1 were developed for IRI prediction[2].

Table 1 IRI Prediction Models from SHRP P-393 Project

Pavement Types	IRI Prediction Models
JPCP (Dowelled)	$IRI = 105.9236 + 159.1279 * AGE / KSTATIC + 2.1669 * JTSPACE - 7.1274 * THICK + 13.4955 * EDGESUP$ $Statistics: N = 21, R^2 = 0.548, SEE = 19.06$
JPCP (Non-Dowelled)	$IRI = 38.8523 + 12.8886 * CESAL + 0.2217 * FT + 1.4979 * PRECIP - 10.9625 * BASE - 13.6880 * SUBGRADE$ $Statistics: N = 28, R^2 = 0.644, SEE = 31.29$
JRCP	$IRI = -141.3723 + 0.8488 * AGE + 0.3469 * PRECIP + 1387.9594 / KSTATIC + 21.2432 * THICK + 15.0920 * EDGESUP$ $Statistics: N = 32, R^2 = 0.782, SEE = 9.86$
CRCP	$IRI = 262.0480 + 1.4706 * CESAL - 2.9432 * THICK - 232.2973 * PSTEEL - 29.7949 * WIDENED - 16.8235 * SUBGRADE$ $Statistics: N = 42, R^2 = 0.546, SEE = 17.1$

Note that US customary unit system was used for these models, in which IRI is in in/mile; CESAL is the accumulated 18-kip ESALs (millions); FT is the average annual freeze-thaw cycles; PRECIP is the average annual precipitations (in.); BASE represents base types (0 for untreated base, 1 for treated base); AGE is the pavement age (years); SUBGRADE is the subgrade type based on AASHTO soil classification (0 for fine-grained soil, 1 for coarse-grained soil). AGE is pavement age (years); KSTATIC is the modulus of subgrade reaction (psi/in.); JTSPACE is the average transverse joint spacing (ft); THICK is slab thickness (in.); EDGESUP represents edge support (0 for AC shoulders, 1 for concrete shoulders); PSTEEL is the longitudinal reinforcement (percent); WIDENED represents lane width type (0 for lane width = 12 ft, 1 for lane width greater than 12 ft). Also note that N is the number of observations; R^2 is the coefficient of determination, and SEE is the standard error of estimates.

The NCHRP Project 20-50(8/13) was conducted to study various factors affecting pavement smoothness using the LTPP General Pavement Studies (GPS) and Specific Pavement Studies (SPS) data[7]. Based on the limited available data, linear mixed effects (LME) models[8] were developed and are summarized in Table 2, in which, IRI is in m/km; IRI_t and IRI_0 represent the IRI at time t and time=0; Time is time (years); f_t is PCC tensile strength (MPa); IRI_{First} is the first available IRI value; IRI_{Last} is IRI at time=ΔTime after the first available IRI; ΔTime is the change in time from first profile data (years); KESAL is cumulative traffic in ESALs (thousands); THICK is PCC thickness (mm); MC is the moisture content of subgrade (percent); TEMP is mean annual ambient temperature (°C); E_c is the elastic modulus of PCC (MPa); Wet.Days is the number of days per year with precipitation exceeding 0.25 mm; SG200 is the percentage of subgrade passing No. 200 sieve; Days32 is the number of days per year with mean temperature greater than 32 °C; and PSTEEL is the longitudinal steel reinforcement (percent). In addition, very low R^2 values and very high residual errors were resulted when using traditional regression analysis in that study.

Table 2 IRI Prediction Models from NCHRP Project 20-50(8/13)

Pavement Types	IRI Prediction Models
JPCP(Dowelled)	$IRI_t = 0.12284 + 0.94229(IRI_0) + 0.05009(Time) - 0.00733(Time \times f_t)$ Section effects standard deviation=0.26, SEE=0.11, No. Section=53
JPCP (Non-Dowelled)	$IRI_{Last} = -0.33172 + 1.15383(IRI_{First}) + 0.00436(KESAL/THICK)$ $+ 0.00418(\Delta Time \times MC_{Subg}) - 0.00178(\Delta Time \times TEMP)$ Section effects standard deviation=0.26, SEE=0.18, No. Section=63
JRCP	$Log_e(IRI_t) = -0.1875633 + 0.3967905(IRI_0) + 0.0000081(KESAL)$ $+ 0.0003266(Time \times MC) + 0.0000002(Time \times E_c)$ Section effects standard deviation=0.15, SEE=0.05, No. Section=52
CRCP (Wet-Freeze)	$IRI_t = -0.4963 + 0.0064(Wet.Days) + 0.0001(E_c/f_t)$ $+ 0.0054(SG200) + 0.0124(Time)$ Section effects standard deviation=0.44, SEE=0.08, No. Section=39
CRCP (Wet-Non-Freeze)	$IRI_t = 2.1952 + 0.0076(Days32) - 2.015(PSTEEL) + 0.0042(Time)$ Section effects standard deviation=0.35, SEE=0.08, No. Section=34

Since roughness is the result of initial as-constructed pavement profile combined with any profile change over time and traffic, certain key distress types which greatly affect IRI measures were chosen as the predictors. In the recommended MEPDG[3], the IRI models as shown in Table 3 were calibrated using LTPP and other field data under a variety of climatic and field conditions, where, *IRI* is the predicted IRI (in/mi); *IRIi* is initial smoothness measured as IRI (in/mi); *CRK* is percent slabs with transverse cracks (all severities); *SPALL* is the percentage of joints with spalling (medium and high severities); *TFAULT* is total joint faulting cumulated per mile (in.); *AGE* is pavement age (years); *FI* is freezing index (°F-days); P_{200} is percent subgrade material passing No. 200 sieve; and *PO* is the number of punchouts per mile at all severities. The site factor $SF = AGE\,(1+0.556*FI)\,(1+P200)*10^{-6}$. No prediction model was proposed for JRCP pavements.

Table 3 IRI Prediction Models from the Recommended MEPDG

Pavement Types	IRI Prediction Models
JPCP	$IRI = IRI_I + C1 \times CRK + C2 \times SPALL + C3 \times TFAULT + C4 \times SF$ $C1 = 0.8203, C2 = 0.4417, C3 = 1.4929, C4 = 25.24$ Statistics: R^2=0.60, SEE=27.3, N=183 (Before Calibration)
CRCP	$IRI = IRI_I + C1 \times PO + C2 \times SF$ $C1 = 3.15,\ C2 = 28.35$ Statistics: R^2=0.60, SEE=14.6, N=94 (Before Calibration)

It is worth mentioning that the prediction of key distress quantities is determined in an incremental manner based on more complicated Axle Load Spectra (ALS) concept [3), 9)]. For example, 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. 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. Therefore, the regression statistics of IRI models after calibration are unknown and questionable.

DATABASE PREPARATION

Initially, the DataPave 3.0 program was used to prepare a database for the study. However, in order to obtain additional variables and the latest updates of the data, the LTPP DataPave Online Release 18.0 became the main source of the study. Of which, only jointed concrete pavements (GPS3 and GPS4) and continuously reinforced concrete pavements (GPS5) were used in the study. Detailed traffic counts and ESALs 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 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[10)]. For this study, the recommendation of dividing the back-calculated modulus of subgrade reaction (or k-value) by 2 as the static k-value was used.

The IRI data was obtained from MON_PROFILE_MASTER 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. 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[11]. The summary, table, cor, plot, pairs, and coplot functions were heavily utilized to summarize the information of interest for this study.

INVESTIGATION OF THE GOODNESS OF FIT OF THE EXISTING MODELS

The aforementioned predictive models given in Table 1 and Table 2 were used for IRI predictions and the results were plotted against the field observed data. Figure 1 depicts the goodness of prediction using SHRP P-393 and NCHRP 20-50(8/13) models, respectively. Visual graphical techniques such as condition plots were used to assist in identifying the factors affecting the goodness of predictions. Apparently, the results were not very favorable. The prediction accuracy of the models from the recommended MEPDG was further investigated. To avoid undesirable misunderstanding of the new guide's prediction algorithm due to the complexity involved, it was decided to use the MEPDG software for IRI predictions directly. For some unknown reasons, the software could not be executed for several randomly selected LTPP sections. Nevertheless, a total of 20 JPCP pavement sections containing 357 data points were successfully analyzed. The goodness of prediction using MEPDG models for IRI is shown in Figure 2. Even though the IRI prediction accuracy appeared to be reasonable, the results of a similar study conducted by Lin[10] for the prediction of joint faulting and transverse cracking was found to be inadequate. Since the adequacy of IRI predictions is heavily relied on the accuracy of distress predictions, knowledge of initial IRI, and site factor adjustment, further study on clarifying this discrepancy is warranted.

(a) (b)

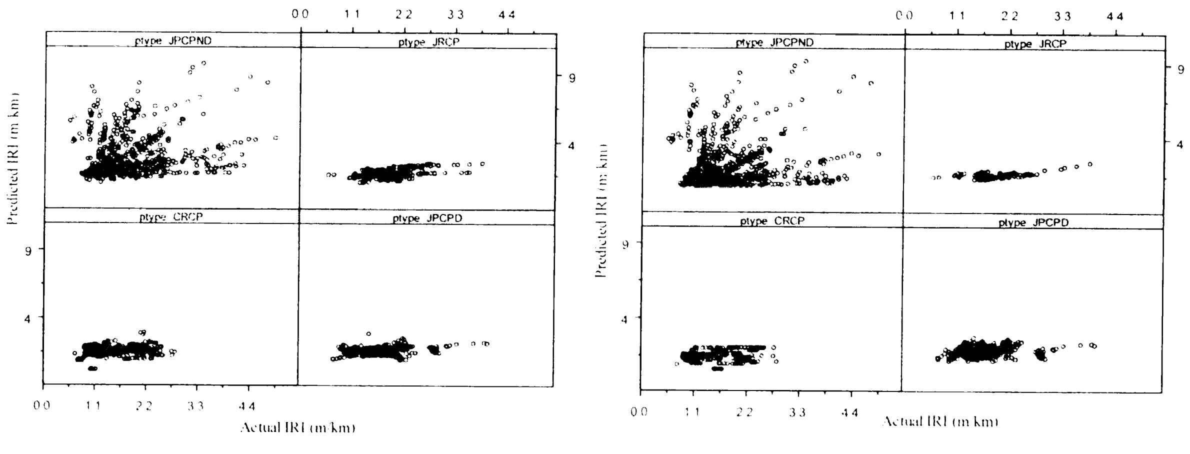

Figure 1 Goodness of prediction using (a) SHRP P-393; and (b) NCHRP 20-50(8/13) models

DEVELOPMENT OF TENTATIVE ROUGHNESS PREDICTION MODELS

Exploratory data analysis of the response variable has indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. Without assuming the error distribution, generalized linear model (GLM) along with quasi-likelihood estimation method was adopted in the subsequent analysis. Many factors included in the aforementioned existing models were considered in the beginning trial analysis. By keeping only those parameters with significant effects in the model, various tentative prediction models were developed.

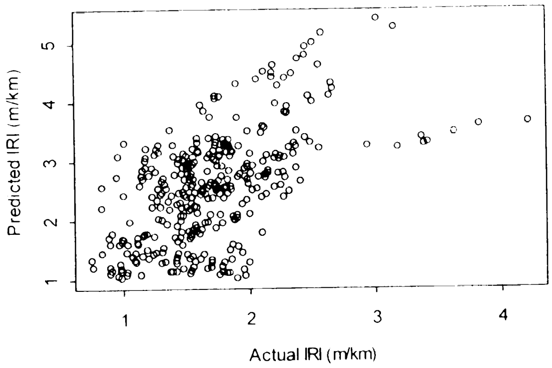

Figure 2 Goodness of fit using MEPDG IRI prediction models

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[11), 12)]. 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 GAM model. Visual graphical techniques were frequently adopted during the modeling process. After considerable amount of trails, the following preliminary models as shown in Table 4 were developed for IRI predictions.

Table 4 Tentative IRI Prediction Models

Pavement Types	IRI Prediction Models
JPCP (Dowelled)	$IRI = 0.4712 + 0.01733 * age + 267.7 * \frac{1}{kstat^2} + 5.736 * \frac{1}{jtspace^2} + 0.1668 * \log_{10}(cesal)$ $+ 0.0004158 * precip + 0.1004 * bt - 0.1809 * subgrade + 0.2473 * widened$ Statistics: R^2=0.35, SEE=0.41, N=380
JPCP (Non-Dowelled)	$IRI = 0.3701 + 0.2758 * \sqrt{age} + 5.5953 * \frac{1}{kstat} - 8.3323 * \frac{1}{jtspace^2}$ $- 304.1814 * \frac{1}{thick^2} + 0.0529 * FT^2 + 0.2985 * \log_{10} precip$ Statistics: R^2=0.231, SEE=0.681, N=605
JRCP	$IRI = -0.554 + 0.1978 * \sqrt{age} + 168.3167 * \frac{1}{kstat^2} + 0.0021 * jtspace^{1.5} + 0.0015 * thick^2$ $+ 0.3166 * \frac{precip}{1000} - 0.528 * \log_{10}(1 + psteel) + 0.431 * \text{edgesup} + 0.0837 * subgrade$ Statistics: R^2=0.4, SEE=0.34, N=416
CRCP	$IRI = 1.9568 + 0.1158 * \sqrt{age} - 112.3738 * \frac{1}{thick^2} - 0.2423 \log_{10}(cesal) + 0.0001 * FT^{1.5}$ $+ 0.4333 * \log_{10} precip - 2.3863 * \sqrt{psteel} + 0.1046 * subgrade - 0.183 * widened$ Statistics: R^2=0.14, SEE=0.44, N=537

In which, age stands for pavement age (years); kstat is the modulus of subgrade reaction (MPa/m); jtspace is joint spacing (m); cesal is cumulated traffic in ESALs (millions); precip is mean annual precipitation (mm); bt is base type (0 for untreated base, 1 for treated base); subgrade is subgrade type (0 for fine-grained soils, 1 for coarse-grained soils); widened is lane width type (0 for width=12 ft, 1 for width>12 ft); thick is slab thickness (cm); FT is yearly freeze-thaw cycles; psteel is the percentage of longitudinal steel reinforcement; edgesup is edge support (0 for AC shoulder, 1 for concrete shoulder); and IRI is the mean roughness (mm). Sensitivity analyses were conducted to assure the predictors of having reasonable physical interpretations. Nevertheless, the effect of slab thickness does not agree with general perceptions that the increase in slab thickness will result in the decrease in roughness. One possible explanation can be that initial roughness may be higher for thicker pavements due to construction problems. To illustrate their goodness of fit, the fitted values were plotted against the observed IRI measures as shown in Figure 3.

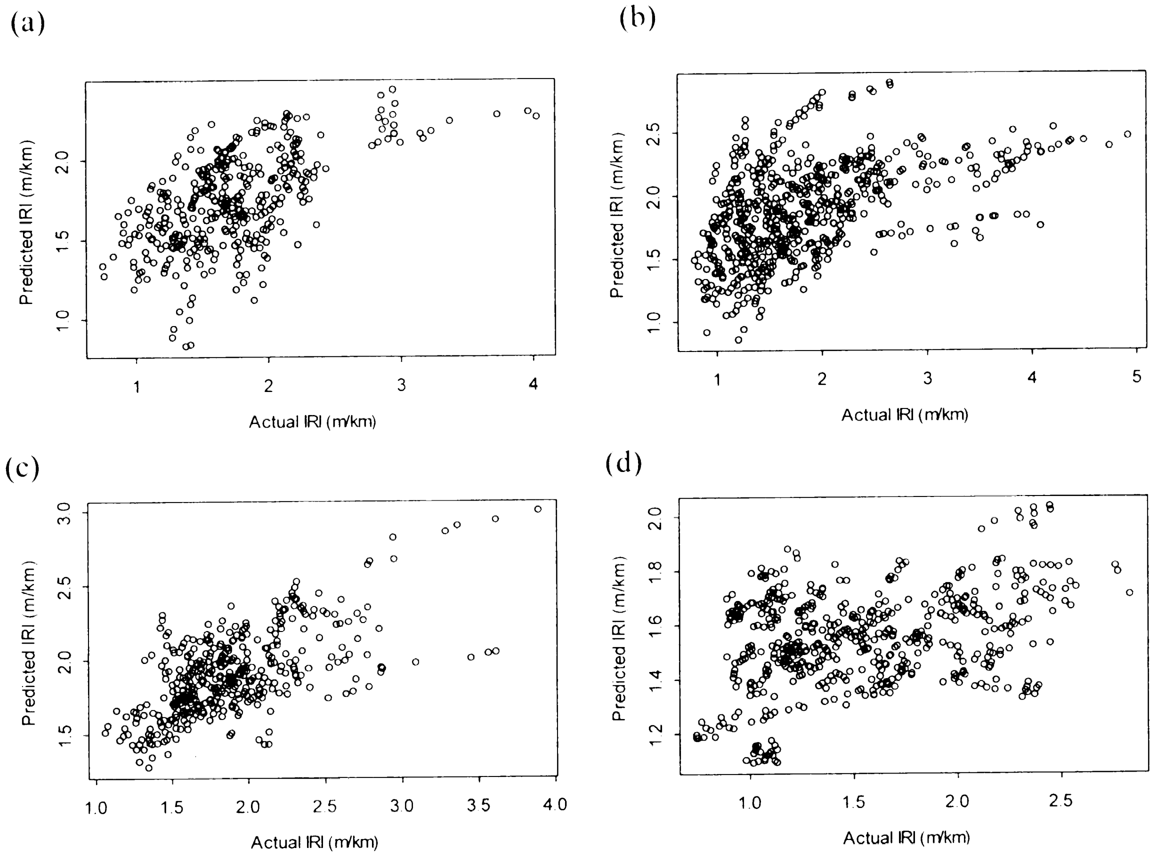

Figure 3 Goodness of fit of the proposed models for (a) JPCP (dowelled); (b) JPCP (non-dowelled); (c) JRCP; and (d) CRCP predictions

CONCLUSIONS

The LTPP DataPave Standard Release 18.0 data was used in this study. The goodness of predictions of the existing roughness models from SHRP P-393, NCHRP 20-50(8/13) and the recommended MEPDG were further investigated. The results of the first two comparisons were not very favorable. In addition, for some unknown reasons, the MEPDG software could not be executed for several randomly selected LTPP sections. Even though the IRI prediction accuracy of the MEPDG appeared to be reasonable, the results of a similar study for the prediction of joint faulting and transverse cracking was found to be inadequate. Since the adequacy of IRI predictions is heavily relied on the accuracy of distress predictions, knowledge of initial IRI, and site factor adjustment, further study on clarifying this discrepancy is warranted.

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 models included several variables such as pavement age, subgrade modulus, joint spacing, cumulated ESALs, annual precipitation, base type, subgrade type, lane width type, slab thickness, yearly freeze-thaw cycles, percent of steel reinforcement, and edge support for roughness predictions. The goodness of the model fit was further examined which also indicated that large variability was still observable in the tentatively proposed models, especially for the JPCP (non-dowelled) and CRCP prediction models. Sensitivity analysis of the explanatory variables has indicated that their general trends seem to be fairly reasonable. Nevertheless, the effect of slab thickness does not agree with general perceptions that the increase in slab thickness will result in the decrease in roughness. One possible explanation can be that initial roughness may be higher for thicker pavements due to construction problems. The tentatively proposed models appeared to reasonably agree with the performance data although their further enhancements are possible and recommended.

ACKNOWLEDGMENTS
This study was sponsored by National Science Council, Taiwan, under the project titled "Development and Applications of Pavement Performance Prediction Models," Phase II (NSC94-2211-E-032-014) and Phase III (NSC95-2211-E-032-061).

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