

New Predictive Modeling Techniques for Pavements

YING-HAUR LEE AND MICHAEL I. DARTER

Statistical regression algorithms have been utilized extensively in pavement engineering for more than three decades. Multiple linear regression, stepwise regression, and nonlinear regression techniques are the most popular ones for pavement predictive modeling. The advantages, the deficiencies, and the limitations of these regression techniques are reviewed. To minimize these problems, the projection pursuit regression (PPR) introduced by Friedman and Stuetzle (1981) was selected to assist in the proper selection of functional forms. Through the use of local smoothing techniques, the PPR attempts to model the response surface as a sum of nonparametric functions of projections of the explanatory variables. The projected terms are essentially two-dimensional curves that can be graphically represented, easily visualized, and properly formulated. As a result a two-step predictive modeling approach is proposed and demonstrated in a case study for the prediction of the edge stress of a pavement slab. It is also demonstrated that statistical regression techniques should not be used alone to obtain a more reliable and comprehensive predictive model. The importance of subject-related engineering knowledge, the principles of dimensional analysis, the proper selection of functional forms, and applicable engineering boundary conditions are considered essential and are also demonstrated. A comparison of the predictive models previously developed and the proposed approach to "prediction" and "extrapolation" clearly shows the preference of the proposed approach and the promising features of the PPR algorithm.

Statistical regression techniques have been utilized extensively in predicting complicated pavement performance indicators for more than three decades. Multiple linear regression, stepwise regression, and nonlinear regression techniques are the most popular ones among transportation engineers. Undoubtedly, regression analysis is a very important statistical tool for many sciences. This paper starts with a review of the advantages and the limitations of these currently used regression techniques. Some specific problems in the selection of proper functional forms and the violation of some embedded statistical assumptions by use of these techniques are discussed.

Traditional parametric regression techniques such as linear and nonlinear regressions require the imposition of a parametric form on the functions and then obtaining the parameter estimates afterward. In situations in which little knowledge about the shape and the form of a function exists, several new nonparametric regression techniques developed over the past 10 years have gradually gained popularity. Without imposing an unjustified parametric assumption, nonparametric regression techniques strive to estimate the actual functional form that best fits the data through the use of scatter plot smoothers (1).

The alternating conditional expectation (ACE) algorithm developed by Breiman and Friedman (2) for optimal transformation

Y.-H. Lee, Department of Civil Engineering, Tamkang University, E725, #151, Ying-Chuan Road, Tamsui, Taipei, Taiwan 25137, Republic of China. M. I. Darter, Department of Civil Engineering, University of Illinois, NCEL #1212, 205 North Mathews Avenue, Urbana, Ill. 61801.

of multiple regression and correlation does an excellent job in maximizing the squared multiple correlation, R^2 (1-3). By using the same alternative backfitting procedures for variable transformations as used in the ACE algorithm, Tibshirani (4) introduced the additivity and variance stabilization (AVAS) algorithm, which tries to achieve the constant error variance assumption of regression (1,4). Both techniques provide an invaluable tool in suggesting proper transformations of variables. However, neither the ACE nor the AVAS algorithm is capable of modeling interactions between the explanatory variables. The variable interactions must be explicitly specified in the assumed model form.

Consequently, the projection pursuit regression (PPR) introduced by Friedman and Stuetzle (5) and Friedman (6) is selected because of its ability to handle variable interactions. As a result a two-step predictive modeling approach is proposed and demonstrated in a case study for the prediction of concrete pavement edge stress owing to the finite slab length effect.

The demonstration is based on a comparison between the previous modeling approaches from the zero-maintenance study (7), a stress analysis procedure (8), and the proposed methodology. The importance of incorporating subject-related engineering knowledge such as the use of the principles of dimensional analysis and the proper selection of functional forms is demonstrated. The proposed modeling procedure illustrates how to select a proper functional form through the use of the PPR as well as the aid of graphical representation and visual inspection. Nonlinear regression is used to obtain the parameter estimates for the specified functional forms. The proper selection of initial parameter estimates is also discussed to guarantee convergence of the iterative nonlinear regression routines. The applications of the resulting predictive models to "prediction" and "extrapolation" are also discussed.

MULTIPLE REGRESSION

Multiple regression is one of the most time-honored and widely used regression techniques for the study of linear relationships among a group of measurable variables. Suppose there exists a true model to describe the relationship between response variables (y 's) and explanatory variables (or predictors, x 's) (9-11):

$$y_i = x_i^T \beta + \epsilon_i \quad (i = 1, \dots, n) \quad (1)$$

where x_i^T is the i th row of the $(n \times p)$ matrix X of the column of 1's if an intercept and the explanatory variables are included. The superscript T denotes the transpose of the column vector x_i . β is a $p \times 1$ vector of unknown regression coefficients, and p and n are the number of parameter estimates in the model and the total number of observations, respectively.

4 五年内代录
(5) 著作 (二)

The basic assumptions are usually that the random errors (ϵ 's) are mutually uncorrelated and normally distributed with zero mean and constant variance and are additive and independent of the expectation function. For any arbitrary β value of $\hat{\beta}$, the residuals $r_i(\hat{\beta})$ can be determined by the following expression:

$$r_i(\hat{\beta}) = y_i - x_i^T \hat{\beta} \quad (i = 1, \dots, n) \quad (2)$$

On the basis of the above assumptions multiple regression tries to find a set of parameters $\hat{\beta}$ such that the sum of the squared residuals given in Equation 3 is minimized, which is also best known as the least-squares (LS) method.

$$RSS(\hat{\beta}) = \sum_{i=1}^n [r_i^2(\hat{\beta})] = r_1^2(\hat{\beta}) + r_2^2(\hat{\beta}) + \dots + r_n^2(\hat{\beta}) \quad (3)$$

The LS method is best known and most frequently adopted because of its simple structure, elegant LS theory, fast computation time, as well as its estimators, which can be obtained explicitly from the data and are interpretable to its user.

As far as variable selection is concerned, all-subset regression and stepwise regression techniques are often utilized for automatic variable selection for preliminary and exploratory analyses of linear relationships among a group of important variables.

ALL-SUBSET REGRESSION AND STEPWISE REGRESSION

All-subset regression procedure finds all possible combinations of variables in the model when the set of candidate variables is not too large. To select the "best" subset of variables, different measurements including the coefficient of determination (R^2), adjusted R^2 ($\text{adj-}R^2$), and the C_p statistics due to Mallows have been proposed (11,12). The Mallows C_p statistic can be defined as follows:

$$C_p = \frac{RSS}{s^2} + 2p - n \quad (4)$$

where RSS represents the residual sum of squares of the regression, p is the number of parameters, and s^2 is the estimate of the residual variance from the full regression model. According to Draper and Smith (12), a regression model with "a low C_p value about equal to p " is preferred such that the model fits the actual data better with the least number of parameters (11,12).

Stepwise regression uses a forward selection or a backward elimination procedure that iteratively adds or deletes one explanatory variable at a time to find the "best" subset of significant independent variables in the model (13). However, this procedure does not necessarily produce the "best" subset among a group of candidate variables. The first variable added or deleted may not necessarily be the best or the worst overall. It is quite possible that the first variable selected by forward selection becomes unnecessary in the presence of the other variables entered afterward or vice versa. In other words, forward selection and backward elimination techniques may result in totally different subsets of variables with similar summary statistics. "It is unlikely that there is a single best subset, but rather several equally good ones," as observed by Gorman and Toman (14).

In comparison with the high computational cost of all-subset regression, stepwise regression is one of the most popular techniques used in transportation research because of its fast computation, simplicity of use, and capability in progressively adding or dropping variables in a regression model. It is expected that some latent or lurking variables may be included in a regression model.

Because of the ease of use and the efficiency of computation, stepwise regression may be easily abused in some respects if one fails to recognize possible physical interpretations on the parameter estimates and the embedded basic assumptions. A very long regression model with dozens of parameter estimates may be the typical result of a stepwise regression that fits the data very well but with no comprehensive engineering insight into the data analyzed. Often, some applicable engineering boundary conditions are violated as well.

NONLINEAR REGRESSION

Practical real-world problems are often found to be nonlinear in nature. Because of its favorable feature of handling a complicated nonlinear model, nonlinear regression has been widely used as a modeling technique for pavement research. In addition, some applicable boundary conditions may be incorporated into the specified nonlinear model form and the parameter estimates may have their own physical meanings as well. However, nonlinear models are more difficult to specify and develop than linear models.

Suppose there exists a true model that best describes the relationship between response variables (y 's) and explanatory variables (x 's) (10,15):

$$y_i = F(\beta, x_i) + \epsilon_i \quad (i = 1, \dots, n) \quad (5)$$

where $F(\beta, x_i)$ is a nonlinear function based on the predictors x_i , β is a $p \times 1$ vector of unknown regression coefficients to be estimated, and n is the total number of observations. Similar to linear regressions, the disturbance (or error) term is usually assumed to be additive, mutually uncorrelated, and normally distributed with zero mean and constant variance. For any arbitrary β value of $\hat{\beta}$, the residuals $r_i(\hat{\beta})$ are

$$r_i(\hat{\beta}) = y_i - F(\hat{\beta}, x_i) \quad (i = 1, \dots, n) \quad (6)$$

Unlike linear regressions whose parameters can be explicitly estimated by a closed-form expression, nonlinear regressions must use an iterative routine to find the best parameter estimates ($\hat{\beta}$) such that the sum of the squared residuals as given in Equation 3 is minimized.

Before carrying out a nonlinear regression, engineers must first assume a feasible descriptive (or conceptual) model form with the most important parameters prespecified on the basis of previous experience and engineering knowledge. In a two-dimensional factor space the model form can be determined as easily as it can be visualized in a scatter plot. Subsequently, reliable parameter estimates may be obtained.

The situation is quite different for the case of multidimensional (three or higher) factor space, where the data trend and the possible interactions among candidate variables cannot be easily identified. Unfortunately, real engineering problems most likely belong to the latter case, in which higher dimensions are concerned and

the true functional forms are rarely known to engineers. Thus, the proper selection of a plausible functional form from a multidimensional factor space provides a real challenge for pavement engineers.

Guessing initial parameter estimates for a multidimensional model is also a very time-consuming process. It is not uncommon that the resulting model does not converge or contains insignificant parameter estimates, with poor initial parameter estimates and an improper model form. In addition, parameter estimates are sometimes toward the wrong direction of their physical interpretations, and they may depend heavily on the initial starting values as well. Specifying bounds for some parameters is not uncommon, although the final resulting model may eventually reach the assumed bounds but without achieving the specified convergence criterion. Thus, "some models are difficult to fit, and there is no guarantee that the procedure will be able to fit the model successfully" (10, p.576).

Furthermore, even when parameter estimates are successfully obtained, the assumption of constant error variance is frequently violated, as indicated by residual analyses. This problem, which is probably due to improper selection of the model form, is often unrecognized, and there is no quick remedy for this situation.

Thus, it is very dangerous to develop such a nonlinear model without acquiring more knowledge of the complicated relationships between the predictors and the dependent variable. The prediction based on an inadequate model specification is also very questionable.

PROJECTION PURSUIT REGRESSION

Unlike the ACE and the AVAS algorithms previously discussed, the projection pursuit regression introduced by Friedman and Stuetzle (5) and Friedman (6) is capable of modeling interactions between predictor variables when suggesting nonparametric transformations to improve the fit. This algorithm is an exploratory nonlinear regression technique that tries to model the response surface (y 's) as a sum of nonparametric functions of projections of the predictor variables (x 's) through the use of super smoothers (5,6). Assume there exists a true model given as follows (16, Vol. 2):

$$y = \bar{y} + \sum_{m=1}^{M_0} \beta_m \Phi_m(a_m^T x) + \epsilon \quad (7)$$

where x is equal to $(x_1, x_2, \dots, x_p)^T$ and denotes the vector of predictor variables and \bar{y} is the expected value (or mean) of the response variable. The "projection" part of the "projection pursuit regression" indicates that the vector of predictors, x , is projected onto the direction vectors, a_m , to get the lengths of the projection $a_m^T x$, where $m = 1, \dots, M_0$. The "pursuit" part indicates that an optimization technique is used to find the best direction vectors, a_m . $\Phi_m(a_m^T x)$ stands for the unknown nonparametric transformation functions of the projected lengths $a_m^T x$ to be estimated. ϵ is the random error. Notice that Φ_m has been standardized to have zero mean and the unity variance given in the following expression:

$$E[\Phi_m(a_m^T x)] = 0 \quad E[\Phi_m^2(a_m^T x)] = 1 \quad (m = 1, \dots, M_0) \quad (8)$$

The PPR algorithm strives to minimize the mean squared residuals, $E[r^2]$, over all possible combinations of β_m , Φ_m , and a_m values. This algorithm first performs a forward stepwise fitting procedure starting with a single term and ending up with M_{\max} terms. Super-smoother is used to estimate the conditional expectation functions. After having fitted the M_{\max} term model in a forward stepwise manner, a backward stepwise procedure is followed and stopped with an M_{\min} term model. Notice that M_{\max} and M_{\min} are the user-specified maximum and minimum number of terms in the model, respectively. The relative importance of each term can be measured by the absolute value of β_m as well. The expectation function of the squared residuals is given as follows:

$$E[r^2] = E \left[y - \bar{y} - \sum_{m=1}^{M_0} \beta_m \Phi_m(a_m^T x) \right]^2 \quad (9)$$

Conceptually, the explanatory variables x 's are projected onto the direction vectors a_1, a_2, \dots, a_m , to find good nonlinear transformations $\Phi_1, \Phi_2, \dots, \Phi_m$ for the multidimensional response surface. In other words, the response surface is broken down into a series of smooth projected terms adding all together. Thus, the largest trend in the factor space is captured as the first projected term Φ_1 , and the residuals become the sources for additional projections afterward. More technical details about the development process, the application, and the demonstration on modeling interactions of the PPR algorithm can be found elsewhere (5,6,16).

PROPOSED TWO-STEP MODELING APPROACH

The proper selection of regression techniques is one of the most important factors in the success of prediction modeling. Since most of the regression algorithms currently available do not directly consider interaction effects during the modeling process, the interaction terms must be subjectively determined prior to performing a regression analysis. With the multidimensional pavement engineering problems in mind, several unresolved deficiencies are frequently identified in the use of stepwise regression and nonlinear regression. These include problems in the selection of correct functional form, violations of the embedded statistical assumptions, and failure to satisfy some engineering boundary conditions as previously discussed.

The projection pursuit regression, however, appears to have the most favorable features in handling these problems. As a result a two-step regression analysis procedure is proposed herein to better find the correct functional form and to better fit the response surface as well.

1. With the help of the PPR a multidimensional response surface is broken down into the sum of several smooth projected curves that are graphically representable in two dimensions. Plausible functional forms and applicable boundary conditions may then be easily identified and specified through visual inspection or engineering knowledge of the physical relationships to model these individual projected curves separately.

2. Traditional parametric regression techniques such as linear and nonlinear regressions are then utilized for these purposes with higher confidence in the parameter estimates.

The overall regression statistics and the goodness of fit often clearly show the advantages of the proposed two-step modeling

approach over the traditional counterparts. The S-PLUS statistical package (16-19), which has been widely used by statisticians, was selected for the analysis due because of the availability of this new regression technique.

EDGE STRESS DUE TO LOADING AND FINITE SLAB LENGTH EFFECTS: CASE STUDY

Since transverse cracking is one of the major structural distresses in jointed concrete pavements, the determination of the maximum bending stress at the longitudinal edge (midway between the transverse joints) is very crucial in any mechanistic or mechanistic-empirical design procedures.

However, the theoretical Westergaard edge stress solution (20) based on an infinite slab assumption may not be well suited for the actual finite slab size conditions. To assess the effect of a finite slab length, a series of finite-element (FE) runs are often performed. Unfortunately, the FE model cannot be easily implemented as a part of a design procedure because of the required running time.

Several attempts in edge stress prediction that proved to be very successful in the past are reviewed and discussed below. The basic concepts behind those analysis procedures were to design and perform a full factorial of FE runs under various combinations of different conditions. Statistical regression techniques were utilized to develop predictive models for different situations. The predictive equations were then used as alternatives for design purposes with sufficient accuracy in estimating stresses.

To demonstrate the proposed two-step predictive modeling procedures, the following case study was performed. The purpose of this case study was to demonstrate the advantages of incorporating dimensional analysis and selecting proper functional forms for the predictive models analyzed. Three different approaches are discussed in the following sections:

1. Use arbitrary but "best" linear combinations of individual variables with interaction terms for regression;
2. Introduce as many mechanistic variables as possible on the basis of engineering knowledge, and also find the "best" linear combinations of these variables with interaction terms for regression; and
3. Introduce as many mechanistic variables (or clusters of variables) as before, and also try to find the best functional forms on the basis of the proposed two-step predictive modeling procedures.

Principles of Dimensional Analysis

According to Westergaard (20,21), the closed-form stress solution due to a circular edge loading on a semi-infinite slab over a dense liquid foundation on the basis of medium-thick plate theory is given as follows:

$$\sigma = \frac{3(1 + \mu)P}{\pi(3 + \mu)h^2} \left[\log_e \frac{Eh^3}{100ka^4} + 1.84 - \frac{4\mu}{3} + \frac{1 - \mu}{2} + 1.18(1 + 2\mu) \frac{a}{l} \right] \quad (10)$$

where

- σ = theoretical Westergaard edge stress (FL^{-2}),
- P = total applied wheel load (F),
- a = radius of the applied circular load (L),
- E = elastic modulus of the concrete slab (FL^{-2}),
- h = slab thickness (L),
- μ = slab Poisson's ratio,
- k = modulus of subgrade reaction (FL^{-3}), and
- l = radius of relative stiffness of the slab subgrade system (L) given by

$$l = \sqrt[4]{\frac{Eh^3}{12(1 - \mu^2)k}} \quad (11)$$

[Note that the basic dimensions are abbreviated as length (L) and force (F).]

Through the use of the principles of dimensional analysis, the above stress equation may be reduced to the following equation form in which both sides of the equation are dimensionless (22,23).

$$\frac{\sigma h^2}{P} = f\left(\frac{a}{l}\right) \quad (12)$$

Therefore, the above normalized stress equation ($\sigma h^2/P$) is simply a function of the dominating variable, a/l , representing the combination effect of the input parameters, namely E , h , k , and a , for constant μ (usually $\mu \approx 0.15$).

To account for the finite slab length effect, Ioannides et al. (21) introduced a normalized length term, L/l , when comparing FE results with the theoretical Westergaard solution. Similarly, a normalized width term, W/l , was introduced to account for the effect of finite slab width. Note that L and W represent slab length and slab width, respectively. However, it is also recognized that the finite slab width effect (W/l) is not as significant as the other two dimensionless parameters (i.e., a/l and L/l), as suggested by earlier investigators (8,23).

An adjustment (or multiplication) factor may be introduced to account for the theoretical difference between the Westergaard solution (σ) and the results from the FE model by using only these two dimensionless factors (a/l and L/l). The adjustment factor (R) is defined by the following expression:

$$R = \frac{\sigma_i}{\sigma} = f\left(\frac{a}{l}, \frac{L}{l}\right) \quad (13)$$

where σ_i is the edge stress determined by the FE model.

The advantages of using the principles of dimensional analysis to derive the above formulation are evident. They can be very helpful in identifying the governing dependent and independent variables (or clustered variables) of a given relationship. In addition, they may also help to reduce the number of factorial FE runs needed for the analysis. The above formulation is not only easy to comprehend but is also dimensionally correct. Thus, the resulting edge stress from FE studies (σ_i) can be determined by multiplying the theoretical Westergaard solution and the adjustment factor (R) together, if it is properly formulated.

Use of Arbitrary Linear Combination of Variables

The analysis of edge stress due to different axle loads, slab lengths, slab thicknesses, foundation supports, thermal gradients, and edge supports was initially studied by Darter (7). A large full factorial of FE runs was performed to determine the edge stresses for different conditions, and subsequently separate predictive models were developed. For the case of loading only, an 18-kip single axle loading was applied on the following factorial pavement sections:

1. Slab length $L = 15, 20, 25,$ and 30 ft;
2. Slab thickness $h = 8, 10,$ and 14 in.;
3. Foundation support $k = 50, 200,$ and 500 pci; and
4. Edge support $ES = 0, 12, 36,$ and 60 in.

where other pertinent input parameters are

$$E = 5 \times 10^6 \text{ psi lb/in}^2,$$

$$W = 12 \text{ ft},$$

$$\mu = 0.15, \text{ and}$$

$$\text{loaded area per wheel} = 12 \times 15 \text{ in}^2.$$

The results of these FE runs were directly used to derive a regression model for edge stress (σ_L) prediction.

Stepwise regression procedure was utilized to pick the "best" linear combinations of individual variables including interaction terms during the modeling process. The slab length (L) was not proved to affect the edge stress prediction significantly and thus was excluded from the model. The proposed predictive model for single axle load without the loss of edge support ($ES = 0$) is given as follows:

$$\sigma_L = \frac{\text{load}}{18 \cdot h^2} \cdot \left(17.35783 - 0.05388 \cdot \frac{h^3}{k} + 7.41722 \cdot \log_{10} \frac{h^3}{k} \right) \quad (14)$$

Using Equation 14 to predict the actual calculated edge stresses from the above FE runs, a fairly good agreement is observed.

However, this model does not contain the elastic modulus of the concrete slab (E) and the finite slab length (L) because of the limitations of the factorial runs conducted. The variables included in this model are numerically significant, but they are not the actual dominating factors with correct dimensions. Thus, the applicability of using this equation beyond the ranges of the data for which the model was originally developed such as different E values and other shorter slabs is very questionable.

Introducing Mechanistic Variables (Clustered Variables)

The analysis of edge stress was further studied by Salsilli-Murua (8). The concept of equivalent single axle radius (ESAR) was utilized for analyzing different load configurations including dual wheels, tandem gears, and tridem gears. The effects of slab sizes, widened outer lanes or tied shoulders, subbase and subgrade layers, and thermal curling were also analyzed separately. Through the use of the principles of dimensional analysis, a series of small

factorial FE runs covering most practical engineering conditions were performed and separate predictive models were developed.

As previously discussed, the effects of wheel loading and finite slab length can be best represented by two dimensionless factors: a/l and L/l . Thus, only a minimum number of factorial FE runs on the basis of these two factors were performed. The adjustment (or multiplication) factor (R) as defined in Equation 13 was also introduced for edge stress prediction. Note that the Westergaard solution (σ) for infinite slab condition is approximated by the resulting ILLI-SLAB edge stress (σ_w) for $L/l = 7.0$ herein when calculating the adjustment factor ($R = \sigma_i/\sigma_w$).

A multiple stepwise regression procedure was utilized again because of its favorable feature of progressively adding and dropping variables in a regression model. The proposed predictive model is given as follows:

$$R = 0.582282 - 0.533078 \left(\frac{a}{l} \right) + 0.181706 \left(\frac{L}{l} \right) - 0.019824 \left(\frac{L}{l} \right)^2 + 0.109051 \left(\frac{a}{l} \right) \left(\frac{L}{l} \right) \quad (15)$$

Statistics: $N = 12, R^2 = 0.996, SEE = 0.0028, CV = 0.29$ percent
Limits: $3 \leq L/l \leq 5, 0.05 \leq a/l \leq 0.3$

N is number of datum points, R^2 is the coefficient of determination, SEE is the standard error of estimates, and CV is the coefficient of variation).

His work has repeatedly demonstrated the advantages of using dimensional analysis to discover the underlying dominating factors for the analysis. In addition, the proposed predictive model not only has fairly good agreement with the data analyzed, but it may also be applied to a wide range of input parameters (i.e., $E, h, k,$ and a). This model is also dimensionally correct. The prediction of edge stress is simply a matter of multiplying the theoretical Westergaard solution by the predicted R value on the basis of this model.

Nevertheless, the conclusions should be restricted to the ranges of the data for which the model was originally developed. This is also true for any regression technique chosen to develop such a predictive model. Besides, a reasonable doubt is raised as to the adequacy of the functional form, especially when an asymptotic trend of the relationship between R and L/l is observed. This asymptotic trend could not be captured simply because of the multiple stepwise regression technique chosen. Thus, the usefulness of the model beyond the specified limits is highly questionable.

Selecting Proper Functional Forms

The importance of incorporating subject-related engineering knowledge into the modeling process, as has been done in the previous example in identifying dominating clustered variables, cannot be overemphasized. In addition, the selection of proper functional forms to satisfy some applicable engineering boundary conditions is a crucial component of a successful predictive model. The proposed two-step modeling approach was adopted herein to illustrate this point. The following factorial ILLI-SLAB runs were performed:

$a/l: 0.05, 0.1, 0.2,$ and 0.3 and

$L/l: 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 6.0,$ and $7.0.$

Note that W/l was set to 7.0 for all runs. The FE grids were generated according to the recommendations of Ioannides (24, pp. 187-188) to provide sufficient accuracy. The pertinent input parameters and the results of these factorial runs are presented in Table 1. A three-dimensional perspective plot providing a very clear picture of the relationship among R , a/l , and L/l is shown in Figure 1.

Because the relationship is a nonlinear three-dimensional surface, a nonlinear regression model may be better suited for this prediction purpose than an arbitrarily selected linear or polynomial model form. But, what kinds of functional forms to be used in the model and how to choose a proper one remain unanswered.

The proposed two-step modeling approach is aimed at search-

TABLE 1 ILLI-SLAB Runs on Slab Size Effects

a/l	L/l	c	a	P	l	L	W	E	k	h	σ
0.05	2.0	2.5	1.995	1250	39.89	79.79	279.26	5	200	10.59	40.868
0.05	2.5	2.5	1.995	1250	39.89	99.74	279.26	5	200	10.59	43.559
0.05	3.0	2.5	1.995	1250	39.89	119.68	279.26	5	200	10.59	45.458
0.05	3.5	2.5	1.995	1250	39.89	139.63	279.26	5	200	10.59	46.744
0.05	4.0	2.5	1.995	1250	39.89	159.58	279.26	5	200	10.59	47.536
0.05	4.5	2.5	1.995	1250	39.89	179.52	279.26	5	200	10.59	47.973
0.05	5.0	2.5	1.995	1250	39.89	199.47	279.26	5	200	10.59	48.180
0.05	6.0	2.5	1.995	1250	39.89	239.37	279.26	5	200	10.59	48.287
0.05	7.0	2.5	1.995	1250	39.89	279.26	279.26	5	200	10.59	48.293
0.10	2.0	5.0	2.821	2500	28.21	56.42	197.47	4	300	8.23	100.494
0.10	2.5	5.0	2.821	2500	28.21	70.52	197.47	4	300	8.23	109.154
0.10	3.0	5.0	2.821	2500	28.21	84.63	197.47	4	300	8.23	115.240
0.10	3.5	5.0	2.821	2500	28.21	98.73	197.47	4	300	8.23	119.399
0.10	4.0	5.0	2.821	2500	28.21	112.84	197.47	4	300	8.23	121.952
0.10	4.5	5.0	2.821	2500	28.21	126.94	197.47	4	300	8.23	123.347
0.10	5.0	5.0	2.821	2500	28.21	141.05	197.47	4	300	8.23	123.999
0.10	6.0	5.0	2.821	2500	28.21	169.26	197.47	4	300	8.23	124.304
0.10	7.0	5.0	2.821	2500	28.21	197.47	197.47	4	300	8.23	124.311
0.20	2.0	10.0	5.642	10000	28.21	56.42	197.47	3	400	9.97	178.536
0.20	2.5	10.0	5.642	10000	28.21	70.52	197.47	3	400	9.97	201.014
0.20	3.0	10.0	5.642	10000	28.21	84.63	197.47	3	400	9.97	216.928
0.20	3.5	10.0	5.642	10000	28.21	98.73	197.47	3	400	9.97	227.837
0.20	4.0	10.0	5.642	10000	28.21	112.84	197.47	3	400	9.97	234.529
0.20	4.5	10.0	5.642	10000	28.21	126.94	197.47	3	400	9.97	238.158
0.20	5.0	10.0	5.642	10000	28.21	141.05	197.47	3	400	9.97	239.822
0.20	6.0	10.0	5.642	10000	28.21	169.26	197.47	3	400	9.97	240.510
0.20	7.0	10.0	5.642	10000	28.21	197.47	197.47	3	400	9.97	240.443
0.30	2.0	10.0	5.642	10000	18.81	37.61	131.64	2	500	7.16	251.011
0.30	2.5	10.0	5.642	10000	18.81	47.02	131.64	2	500	7.16	292.598
0.30	3.0	10.0	5.642	10000	18.81	56.42	131.64	2	500	7.16	322.461
0.30	3.5	10.0	5.642	10000	18.81	65.82	131.64	2	500	7.16	342.758
0.30	4.0	10.0	5.642	10000	18.81	75.23	131.64	2	500	7.16	355.316
0.30	4.5	10.0	5.642	10000	18.81	84.63	131.64	2	500	7.16	362.178
0.30	5.0	10.0	5.642	10000	18.81	94.03	131.64	2	500	7.16	365.327
0.30	6.0	10.0	5.642	10000	18.81	112.84	131.64	2	500	7.16	366.408
0.30	7.0	10.0	5.642	10000	18.81	131.64	131.64	2	500	7.16	365.845

a = radius of loaded area, in.

c = load dimensions are $c \times c$, except those cases with $c = 2.5$ use $2c \times c$ instead, in.

l = radius of relative stiffness, in.

h = slab thickness, in.

E = elastic modulus of concrete, $\times 10^6$ psi

k = modulus of subgrade reaction, pci

L = slab length, in.

W = slab width, in.

P = total applied load, lb

σ = edge bending stress, psi

The tire pressure was held constant at 100 psi for all the runs.

Note: 1 inch = 2.54 cm, 1 psi = 6.89 kPa, 1 pci = 0.27 MN/m³, 1 lb = 0.454 kg.

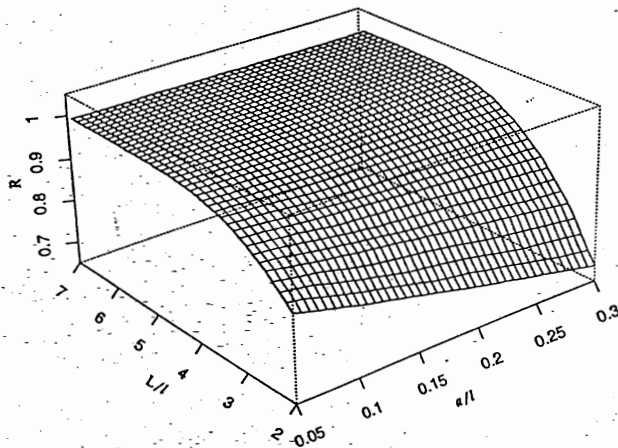


FIGURE 1 Slab size effect: three-dimensional plot.

ing for a series of two-dimensional projected curves first to ease these important modeling decisions. First, the PPR technique was utilized to determine the direction vectors for a/l and L/l and the suggested single-term nonlinear transformation $\Phi_1(a_l^T x)$ by using only those datum points within the specified limits of Equation 15. The results of this PPR trial are given in the following equations:

$$R = 0.9667 + 0.0330\Phi_1(ATX1) \quad (16)$$

$$ATX1 = -0.8945\frac{a}{l} + 0.4471\frac{L}{l} \quad (17)$$

A graphical representation of this PPR trial is shown in Figure 2. The first two plots are the scatter plots of the one-to-one relationships of R versus a/l and L/l . The next plot shows the resulting first PPR projected term versus the length of the projection, that is, $\Phi_1(a_l^T x)$ versus $a_l^T x$. Notice that $a_l^T x$ is represented by the axis label ATX1, whereas $\Phi_1(ATX1)$ is represented by the axis label "1st Projected Term" in this plot. The goodness-of-fit of this PPR model including a plot of the predicted versus actual values and a plot of the residual versus predicted values is displayed in the last two plots. If this curve is properly modeled and the above two equations are used, fairly good predictions with a relatively high R^2 of 0.995 may be obtained.

Thus, the task was reduced to simply finding a feasible model for this projected curve. An asymptotic trend was clearly identified through visual inspection. Therefore, an asymptotic nonlinear model with two to three (or at most four) parameters may describe this curve adequately. The following four-parameter equation form was selected to offer the maximum flexibility in the modeling process:

$$\Phi_1(ATX1) = a_1 + \frac{1}{a_2 + a_3 ATX1^{a_4}} \quad (18)$$

The nonlinear regression technique was then used to obtain the parameter estimates. The first derivative of this equation form with respect to each parameter was also provided to help the iterative regression routine converge faster. The starting value of each parameter was carefully chosen so that a_1 and a_4 were large negative values, for example, -4.0 , and a_1 was the minimum possible

value of Φ_1 . Since a_2 and a_3 were still undecided, two small positive values, for example, 0.01, were chosen as their starting points. The following equation satisfies the convergence criteria even with many other different starting values:

$$\Phi_1(ATX1) = -5.5869 + \frac{1}{0.1473 + 0.2627ATX1^{-5.1659}} \quad (19)$$

The overall statistics for the prediction of R (or σ_f/σ_w) because of the slab length effect by using Equations 16, 17, and 19 are summarized as follows:

Statistics: $N = 20$; $R^2 = 0.994$; $SEE = 0.0027$, $CV = 0.28$ percent
Limits: $3 \leq L/l \leq 5$, $0.05 \leq a/l \leq 0.3$

To illustrate how the three-dimensional response surface (Figure 1) might be broken down into the sum of a series of two-dimensional curves, the PPR algorithm was utilized again to obtain a two-term model and a three-term model as shown in Figures 3 and 4, respectively. By analogy, the axis labels "ATX2" and "ATX3" represent $a_2^T x$ and $a_3^T x$, respectively, whereas the axis labels "2nd Projected Term" and "3rd Projected Term" represent $\Phi_2(ATX2)$ and $\Phi_3(ATX3)$ in Equation 7, respectively. The other plots are similar to the plots defined in Figure 2.

As an example, the results of the two-term PPR model are given in the following equations:

$$R = 0.9667 + 0.0330\Phi_1(ATX1) + 0.00210\Phi_2(ATX2) \quad (20)$$

$$ATX1 = -0.8945\frac{a}{l} + 0.4471\frac{L}{l} \quad (21)$$

$$ATX2 = 0.9970\frac{a}{l} + 0.07787\frac{L}{l} \quad (22)$$

The second projected term contributes little to the prediction of R , since its coefficient is very small when compared with the coefficient of the first projected term (i.e., $\beta_2 = 0.0021$, whereas $\beta_1 = 0.0330$). The third projected term also contributes very little to the accuracy of the prediction when compared with the first one and the second one, and thus the associated equations for the three-term model are not presented herein. In fact, the use of only one or two projected curves can adequately describe this three-dimensional response surface, as suggested by these figures.

The plausible model forms suggested by these PPR trials are an asymptotic nonlinear model for the first projected curve, a second-degree polynomial for the second projected curve, and a third-degree polynomial for the third projected curve if necessary. Of course, some piecewise linear and nonlinear curves may also be formulated for these purposes without much loss of generality.

Prediction and Extrapolation

From the above demonstration, it is evident that using different regression procedures may result in totally different predictive models, but with excellent agreement with the same set of data.

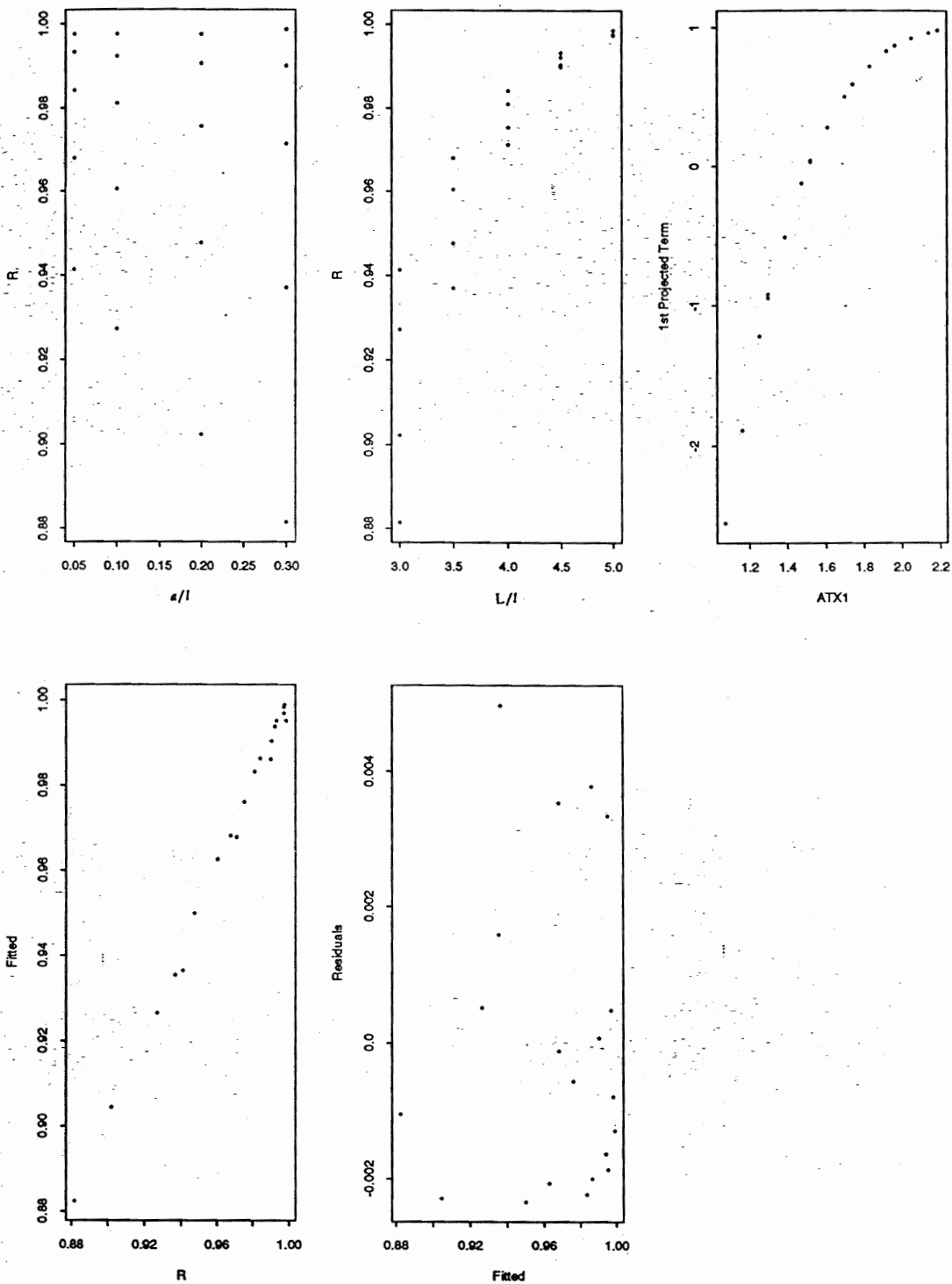


FIGURE 2 Slab size effect: one-term PPR model.

Under the umbrella of statistical regression analysis, they are all feasible solutions of the targeted problem as long as the conclusions are restricted to the range of the data. In other words "extrapolation beyond the range of the data" is never considered feasible with statistical regression analysis procedures.

However, it is also recognized that "extrapolation" is often necessary in actual engineering practice because of the limited

resources available and technical limitations. To judge which equation is preferable, both Equations 15 and 16 were checked by plotting the predicted versus the actual R values within the specified data ranges as displayed by the symbol "o" in Figures 5(a) and 5(b), respectively. It is clearly shown that both equations result in very good predictions within the range of the data from which they were originally developed. In addition, Figures 5(a)

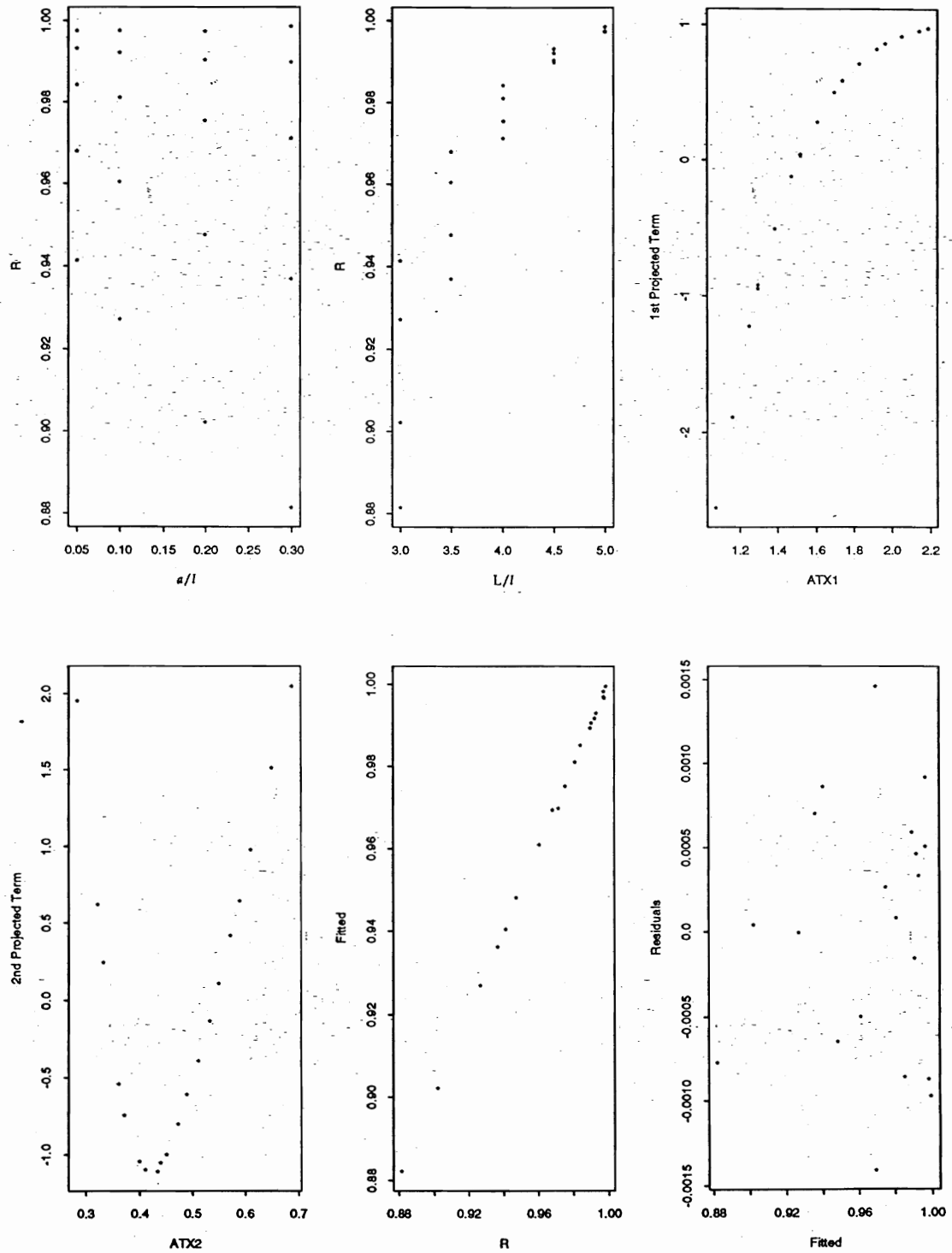


FIGURE 3 Slab size effect: two-term PPR model.

and 5(b) present the results when extrapolating beyond the specified limits by using these two models and the data from all of the 36 FE runs, respectively. These datum points, as displayed by the symbol “*” in the graphs, clearly show the difference.

Extrapolation by using Equation 15 results in totally unacceptable predictions outside the specified limits as shown in Figure 5(a). However, this problem is less pronounced as shown in Fig-

ure 5(b) when using Equation 16. In fact, the extrapolation of L/l greater than 5.0 provides excellent agreements with the actual data, since the functional form was properly selected to be asymptotic such that the predicted R values are very close to unity, as they should be. Nevertheless, some discrepancies still exist when extrapolating Equation 16 to smaller L/l values, that is, $L/l < 3.0$, which generally result in smaller R values.

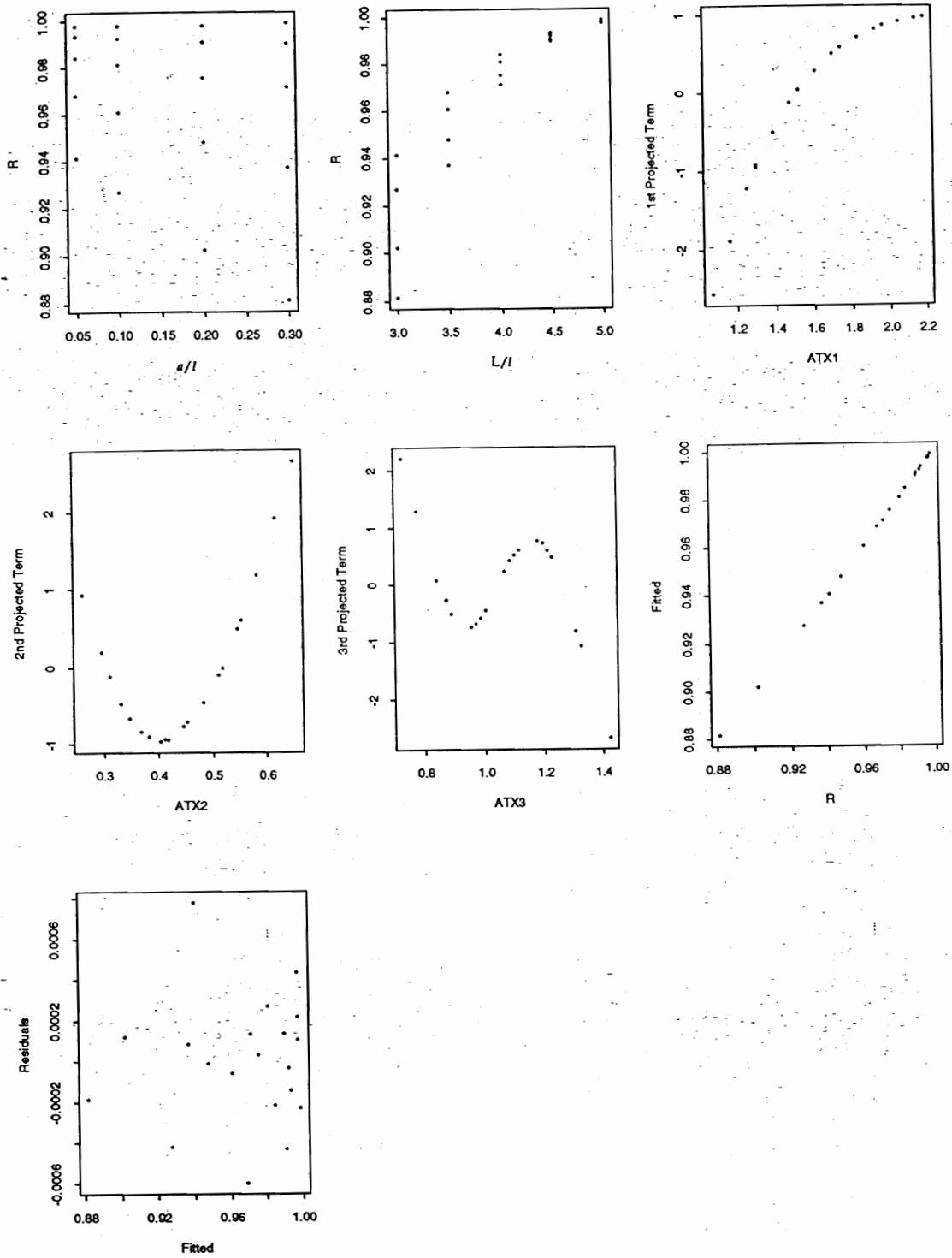


FIGURE 4 Slab size effect: three-term PPR model.

This result may be explained by the fact that the first parameter $[a_1, \text{ or the minimum possible value of } \Phi_1(\text{ATX1})]$ of Equation 19 was estimated to be -5.5869 , such that Equation 16 will never result in a value below 0.7823 . This approximation is acceptable for the ranges of data that were used to develop Equations 16, 17, and 19. However, it may not be as accurate when extrapolating too far away from this specified range. If the minimum possible

value of R is known, this boundary condition may also be imposed on the predictive model. Thus, better agreement with the data can be obtained even in the case of extrapolation.

In summary, this case study not only demonstrates the benefits of using mechanistic variables through the use of the principles of dimensional analysis but it also emphasizes the importance of selecting proper functional forms. Correct functional forms pro-

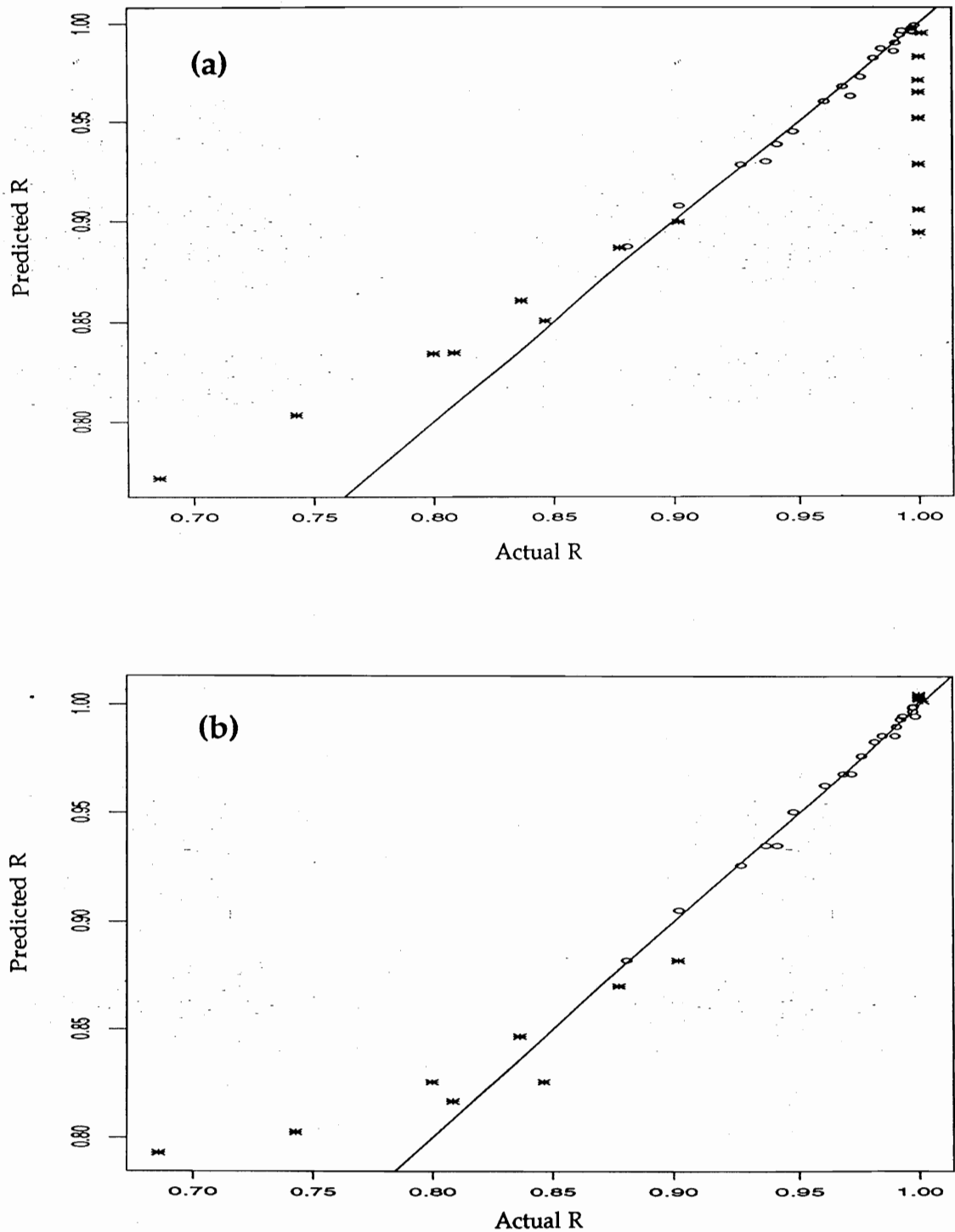


FIGURE 5 Extrapolated prediction plots using (a) existing model; (b) new model.

vide more comprehensive insights into the performance of the predictive model and may also lead to reasonable results even when extrapolation beyond the range of the data is required. It can be concluded that proper functional form is also a very crucial component in the success of a modeling process. The proper selection of functional forms to satisfy some applicable physical boundary conditions and subject-related engineering knowledge are the best supplements to statistical regression algorithms.

CONCLUSIONS

Several traditional linear and nonlinear regression techniques that have been widely adopted in pavement research were reviewed. Their advantages and limitations were discussed. Application of these regression techniques to practical engineering problems often shows the deficiencies in the selection of proper functional forms, the violation of some embedded statistical assumptions,

and failures to satisfy some applicable engineering boundary conditions.

Through the use of projection pursuit regression technique, a two-step predictive modeling approach was proposed in an attempt to minimize these problems. The proposed modeling approach was demonstrated in a case study for edge stress prediction owing to the finite slab length effect. Without imposing an unjustified parametric assumption, the PPR provides a unique routine for breaking down higher-dimensional engineering problems into a series of sensible projected curves. By doing so the individual projected curves may be formulated separately with better choices of feasible functional forms as well as possible boundary conditions. Not only did the demonstration reemphasize the advantages of using the principles of dimensional analysis but it also illustrated the importance of the proper selection of functional forms. Correct functional form provides more comprehensive insights into the performance of the predictive equation and may also lead to reasonable results even when extrapolation beyond the range of the data is required.

The demonstration was based on the data from the theoretical FE solutions in which no erroneous data are expected. As for applying the PPR to field or laboratory data with some possible errors, the promising features of the PPR algorithm are also helpful for identifying any extremely strange behavior because of data errors. Engineering knowledge of the physical mechanism of the problem may be applied in identifying the possible bad datum points as well.

It is also believed that only through the application of both engineering and statistical knowledge and techniques will a more theoretically correct predictive equation be developed. If properly developed it may also be applied beyond the range of the data. Nevertheless, the conclusions should be restricted to the range of the data.

ACKNOWLEDGMENTS

This research work was partially sponsored by the Illinois Department of Transportation under the project titled Implementation of Illinois Pavement Feedback System, for which different modern regression techniques were utilized for predictive model development. The authors would like to express much appreciation to James Hall, Illinois Department of Transportation, for valuable assistance in this project.

REFERENCES

- Hastie, T. J., and R. J. Tibshirani. *Generalized Additive Models*. Monographs on Statistics and Applied Probability 43. Chapman & Hall, 1990.
- Breiman, L., and J. H. Friedman. Estimating Optimal Transformations for Multiple Regression and Correlation (with Discussion). *Journal of the American Statistical Association*, Vol. 80, 1985, pp. 580-619.
- Buja, A. Remarks on Functional Canonical Variates, Alternating Least Squares Methods and ACE. *Annals of Statistics*, Vol. 18, No. 3, 1990, pp. 1032-1069.
- Tibshirani, R. Estimating Transformations for Regression via Additivity and Variance Stabilization. *Journal of the American Statistical Association*, Vol. 83, 1987, pp. 394-405.
- Friedman, J. H., and W. Stuetzle. Projection Pursuit Regression. *Journal of the American Statistical Association*. Vol. 76, 1981, pp. 817-823.
- Friedman, J. H. *SMART User's Guide*. Technical Report No. 1. LCS, Department of Statistics, Stanford University, Stanford, Calif., 1984.
- Darter, M. I. *Design of Zero-Maintenance Plain Jointed Concrete Pavement, Vol. I. Development of Design Procedures*. FHWA Report FHWA-RD-77-111. FHWA, U.S. Department of Transportation, June 1977.
- Salsilli-Murua, R. A. *Calibrated Mechanistic Design Procedure for Jointed Plain Concrete Pavements*. Ph.D. thesis. University of Illinois, Urbana, 1991.
- SAS User's Guide: Basics*, Version 5 edition. SAS Institute, Inc., 1985.
- SAS User's Guide: Statistics*, Version 5 edition. SAS Institute, Inc., 1985.
- Weisberg, S. *Applied Linear Regression*, 2nd ed. Wiley Series in Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York, 1985.
- Draper, N. R., and H. Smith. *Applied Regression Analysis*, 2nd ed. Wiley Series in Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York, 1981.
- Rousseeuw, P. J., and A. M. Leroy. *Robust Regression and Outlier Detection*. Wiley Series in Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York, 1987.
- Gorman, J. W., and R. J. Toman. Selection of Variables for Fitting Equations to Data. *Technometrics*, Vol. 8, 1966, pp. 27-51.
- Bates, D. M., and D. G. Watts. *Nonlinear Regression Analysis and Its Applications*. Wiley Series in Probability and Mathematical Statistics. John Wiley & Sons, Inc., New York, 1988.
- S-PLUS User's Manual*, Vol. 1 and Vol. 2. Statistical Sciences, Inc., Seattle, Wash., Nov. 1991.
- S-PLUS Reference Manual*. Statistical Sciences, Inc., Seattle, Wash., Nov. 1991.
- Chambers, J. M., and T. J. Hastie. *Statistical Models in S*. Wadsworth & Brooks/Cole Computer Science Series. AT&T Bell Laboratories, 1992.
- Becker, R. A., J. M. Chambers, and A. R. Wilks. *The New S Language—A Programming Environment for Data Analysis and Graphics*. The Wadsworth & Brooks/Cole Computer Science Series. AT&T Bell Laboratories, 1988.
- Westergaard, H. M. New Formulas for Stresses in Concrete Pavements of Airfields. *Transactions, ASCE*, Vol. 113, pp. 425-444, 1948. Also in *Proceedings, ASCE*, Vol. 73, No. 5, May 1947.
- Ioannides, A. M., M. R. Thompson, and E. J. Barenberg. The Westergaard Solutions Reconsidered. In *Transportation Research Record 1043*, TRB, National Research Council, Washington, D.C., 1985.
- Tayabji, S. D., and D. J. Halpenny. Thickness Design of Roller-Compacted Concrete Pavements. In *Transportation Research Record 1136*, TRB, National Research Council, Washington, D.C., 1987.
- Ioannides, A. M., and R. A. Salsilli-Murua. Temperature Curling in Rigid Pavements: An Application of Dimensional Analysis. In *Transportation Research Record 1227*, TRB, National Research Council, Washington, D.C., 1989.
- Ioannides, A. M. *Analysis of Slabs-on-Grade for a Variety of Loading and Support Conditions*. Ph.D. thesis. University of Illinois, Urbana, 1984.

Publication of this paper sponsored by Task Force on Statistical Methods in Transportation.