applicability of the AASHO Road Test data. One of the findings of this preliminary study is the need for a more comprehensive, realistic, and consistent data base before useful relationships between distress and performance are analytically possible. This can be accomplished with the cooperation of state, provincial, and regional highway agencies through improved behavior monitoring and documentation practices. Specifically, highway engineers should attempt to schedule periodic evaluation on homogeneous pavement sections at regular intervals of time. The technology now exists to measure and make computerized, "manageable" records of a number of pavement behavior parameters continuously and simultaneously at great savings in both time and money. Seasonal effects play an important role in characterizing pavement behavior patterns and, therefore, it is desirable to monitor behavior more than once a year on each pavement section.

7. The measurement of cracking is still a highly subjective operation, as evidenced by the numerous inconsistencies and high variability of the AASHO Road Test cracking data. Not only is there a need for more objective crack-measurement techniques, but in addition the definition of cracking should reflect the physical behavior, not the hypothesized cause or mechanism. There is also a need for uniformity among different agencies in the definitions of cracking and other forms of pavement behavior. Such consistency and cooperation would aid in the development of a more comprehensive data base from which pavement distress-performance relationships could ultimately be developed.

8. The modeling approach presented in this paper is equally applicable to pavement types other than flexible pavements. Rigid pavements and also new types such as sulfur-extended asphalt pavements should be included in future investigations.

9. In considering pavement deterioration as a stochastic process, the performance of maintenance is an intervention in that process. Intervention analysis is a statistical technique for determining whether a known intervention significantly alters the behavior of a stochastic process. This is a potential means of evaluating the effectiveness of various types of maintenance or rehabilitation strategies.

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Requirements for Reliable Predictive Pavement Models

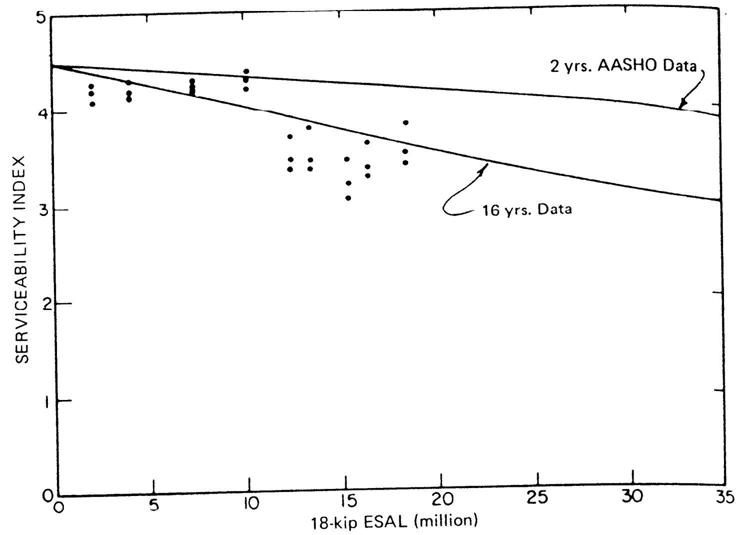
MICHAEL I. DARTER

The general requirements for reliable pavement prediction models are presented. Performance models are essential for efficient management of pavements. Experience has shown that they can best be derived from a data base of in-service pavements. The major requirements of a reliable model for predicting performance, herein defined as serviceability index and distress occurrence over time, are (a) an adequate data base built from in-service pavements, (b) the inclusion of all variables (including mechanistic variables) that significantly affect performance, and (c) an adequate functional form of the model that considers shape, nonlinearities, and interactions; meets boundary conditions; and provides reasonable sensitivity of variables. The model must also meet statistical criteria for precision (e.g., error of prediction, R^2, and regression coefficients).

This paper describes the requirements and general development of reliable pavement performance models derived from a data base of in-service pavement information. Pavement management requires the use of performance models for design of new pavements as well as the maintenance and rehabilitation of older pavements. Data from in-service pavements are also needed for use in establishing the validity or in calibrating predictive design models derived from mechanistic concepts. The resulting designs will only be as reliable as the models used in their development; thus, their accuracy and capability are very important.

Predictive performance models can conceivably be mechanistic in nature when the relationship between the dependent and independent variables is exactly known (e.g., F = ma). However, the prediction of the present serviceability index (PSI), pavement condition index (PCI) (1), and distress history depend on many variables in extremely complex ways. Thus, the only practical predictive model that can be developed is an empirical model (or semiempirical model with some mechanistic input) based on measured data. Multiple regression techniques are commonly used to develop empirical predictive models. This paper is limited to the development of linear regression models and to the requirements of

Figure 1. Illustration of original prediction model based on 2 years' data and new prediction model based on 16 years' data.



reliable models derived from a data base of information from in-service pavements.

Typical linear regression models take the following general form:

$$\hat{Y} = a_0 + a_1X_1 + a_2X_2 + \ldots a_nX_n \quad (1)$$

where

$\hat{Y}$ = estimated value of the dependent variable Y (performance indicator such as PSI, PCI, or distress),

$X_1, X_2, \ldots, X_n$ = value of the independent variables (such as layer thickness, material properties, climatic parameters, and traffic factors), and

$a_0, a_1, a_2, \ldots, a_n$ = parameters of the model estimated by regression.

The difference between the measured value Y and the estimated value $\hat{Y}$ from Equation 1 for each data case is called a residual or the error in prediction: Residual = $Y - \hat{Y}$. The regression procedure involves the selection of a_0, a_1, a_2, ... so that the sum of the squared residuals over all the data is minimized. Since the sum of squared residuals is minimized, the process is called least squares. Thus, no other line is closer to all the data points. This paper is not intended to provide a detailed statistical description of regression analysis but to discuss key practical considerations in developing predictive models.

The major requirements of a reliable model for predicting performance include an adequate data base, the inclusion of all significant variables that affect performance, an adequate functional form of the model, and the satisfaction of statistical criteria concerning the precision of the model.

ADEQUATE DATA BASE

The most important consideration in developing a reliable performance model is the building of an adequate data base. First and foremost, the data base must be a representation of the overall pavement network that the model is being developed to represent. Next, the data collected must be measured accurately and without bias. Finally, there must be a sufficient number of data cases so that practical and statistical requirements can be satisfied.

Representative Sample

A predictive model may be needed for use in pavement design or rehabilitation over a given geographic area (e.g., a state or nation). Since it is generally impossible to physically measure data from every pavement located in the geographical area, a sample of the data must be selected. Regression analysis is commonly performed on a data sample from which the overall population (or pavement network) parameters can be estimated. The data sample collected, therefore, must be representative of the general geographic region as far as materials, designs, traffic, soils, climate, and age (varying up to the desired design life) go. This fundamental concept of an adequate data base shows that the results from a single road test provide only limited information on which to base a performance model. For example, many persons have criticized the nationwide use of the models derived at the AASHO Road Test under very limited conditions. In fact, analyses conducted on 16 years of data from 25 sections of the Road Test on I-80 showed that the original equations overpredicted performance, as illustrated in Figure 1 (2).

The data base should ideally include data cases (e.g., projects) that contain a sufficient range of each of the variables. For example, if a range of surface thickness is not included, it is impossible to include that variable in the model and to determine its relative influence on performance. A data base constructed as a data factorial with three or more levels of each variable provides a balanced set of data from which to develop a broad-based model, as illustrated in Figure 2. However, because of the nature of in-service pavement data (e.g., messy data), this is usually impossible to completely accomplish. It is helpful, however, to at least use a factorial design in the initial planning of the data collection to provide a data bank as broadly based as possible.

Reliable Data

The overall data to be collected can be divided into

Figure 2. Illustration of factorial data sample to provide balanced information to develop predictive models.

Climate	Design (Slab Thick-cm)	Coarse Grained Soil, Age, Years < 10	Coarse Grained Soil, Age, Years 10-19	Coarse Grained Soil, Age, Years ≥ 20	Fine Grained Soil, Age, Years < 10	Fine Grained Soil, Age, Years 10-19	Fine Grained Soil, Age, Years ≥ 20
WET-NONFREEZE	15						
	20						
	25						
WET-FREEZE	15			1 or more pvt. sect.			
	20						
	25						
DRY-NONFREEZE	15						
	20						
	25						
DRY-FREEZE	15						
	20						
	25						

field information and historical information. The field data are obtained from surveys and measurements on each project. The historical data are obtained from agency records (e.g., traffic, materials, climate, and construction). Sometimes portions of the historical data were never collected on a given project or, if collected, were thrown away or lost. Care must be taken to assure the accuracy of the data obtained from historical records. Field data must be obtained by using carefully developed procedures. In the past, a few agencies have developed field data collection procedures (3-6). Comprehensive procedures have recently been developed and verified for both historical and field data for airfield pavements (1), highway pavements (7-9), and road and street pavements (10). Survey crews can be sufficiently trained to be consistent in data gathering. Equipment must be maintained and kept calibrated so that the measurements do not change over time.

Sufficient Amount of Data

The development of a reliable model requires the collection of a sufficient number of data cases. A case is the basic unit of analysis for which data have been obtained. In terms of pavement engineering, a case could be a single test section or an entire construction project. Each case is composed of one data value for each of the several variables under consideration. For example, a data case could consist of the following data values from a single section of pavement: PSI, alligator cracking, rutting, surface thickness, base thickness, California bearing ratio (CBR) of base, CBR of subgrade, average number of freeze-thaw cycles, deflection, and total accumulated 80-kN (18-kip) equivalent single-axle loads. This set of information would define a single data case.

The actual length of pavement that makes up the case must be carefully defined. For example, a case has been defined in NCHRP Project 1-19 as a uniform section of pavement that has the following uniform characteristics along its length (7): structural design, joint and reinforcement design, proportion of truck traffic, number of lanes, subgrade conditions, construction by same contractor, open to traffic same year, pavement materials, and maintenance applied. In most instances, the uniform section will correspond to a regular construction project. This procedure avoids the problem of having widely varying results within a given data case, which ultimately leads to masking the true effect of the variables involved.

Analysis of field data for a given uniform section in NCHRP Project 1-19 showed that, for individual distress types, a minimum of approximately 10 percent of the uniform section length should be measured. A length of 0.16 km/1.6 km (0.1 mile/mile) is the recommended stratified sampling plan.

It is also important to obtain some replicate data cases. A replicate data case is two or more pavements identically constructed (as far as is known), placed on the same subgrade, and subject to the same climate and traffic. Any difference in performance between the two gives an indication of pure error. The value of this estimate is discussed under statistical criteria.

INCLUSION OF VARIABLES

Identification of Variables

Every possible variable that may affect pavement performance should be considered initially. This list will typically be very large. These variables are then divided into groups such as the following:

1. Data that can be directly measured within acceptable cost and time constraints;
2. Data that are measurable but too expensive or time consuming for regular collection;
3. Data that are not available from records or that cannot currently be measured;
4. Data that are available from historical records on design, construction, performance, traffic, maintenance, and climate; and
5. Data that can be computed or estimated based on the above types of data.

Available time and resources will not generally be sufficient to collect all desired data. However, this process will reveal the major deficiencies and limitations in the models by pointing out the variables that are not included in the model. A practical assessment of which variables can be collected must be made. The question that should be continually asked is, How will the deletion of this variable limit the usefulness of the model? Sometimes, when the direct measurement of a variable is not feasible, another variable that correlates highly with the other variable can be included.

One way to assess the scope of the model is to categorize the variables included under major topics that are known to affect performance, such as layer material properties, subgrade characterization, layer geometry, climate, traffic, jointing, construction (e.g., quality control), maintenance, and drainage. If each of these general topics is adequately represented by one or more variables, then the model should contain most of the important variables known to affect performance.

Mechanistic variables that can be computed by using various pavement structural programs (e.g., elastic layer, finite element) can add significantly to the reliability and utility of the prediction model. For example, in the development of prediction models for asphalt pavements, the strain and stress in various layers could be computed for a given load and temperature and used as a variable in regression. The ratio of tensile stress to strength of the concrete slab can lead to a much improved model.

Variable Selection

The selection of the best regression model to fit a given sample of data requires extensive knowledge about (a) the problem at hand and the measured data and (b) a regression analysis program. Several statistical procedures exist for selecting variables in regression. Several methods are discussed and compared by Draper and Smith (11). The stepwise regression procedure that employs the least-squares method is believed to give the best selection of independent variables. As explained in Draper and Smith (11), the stepwise regression procedure starts with the simple correlation matrix and enters into regression the independent variable (X) most highly correlated with the dependent variable (Y) (e.g., PSI, distress). By using partial correlation coefficients, it then selects (as the next variable to enter regression) that X variable whose partial correlation with the response Y is highest and so on. The procedure reexamines "at every stage of the regression the variables incorporated into the model in previous stages" (11). The procedure does this by testing every variable at each stage as if it entered last and by checking its contribution by means of the partial F test. The process is stopped when essentially no additional variable significantly improves the precision of the model.

A few excellent computerized statistical-analysis packages are available. One of the most well-documented packages and easiest to use for regression and many other analyses is the Statistical Package for the Social Sciences (SPSS) (12).

FUNCTIONAL FORM OF MODEL

The functional form of the model, or the way in which the variables are arranged, has a great effect on its reliability. The functional form must be established through careful thought about the actual relationships between the variables and the plotting of available data (Y versus all X's). The functional form cannot be left to the computer to establish; the researcher must be thoroughly familiar with the data. The reliability of the functional form of the predictive model can be assessed through considering the linearity and additivity of the variables, the boundary conditions, and a sensitivity analysis.

Linearity and Additivity of Variables

Basic linear regression requires that the relationships among the variables are linear and additive as shown by Equation 1. Thus, the relationship between Y and X_i is assumed to be linear and the combined effects of the X's are additive. These assumptions are not generally true for pavement variables. There are, however, methods to handle nonlinear and nonadditive relationships. The three most-often-used methods are briefly described:

1. Transform the original variable so that the new relationship is linear. For example, if the relationship between Y and X_1 is curvilinear, the relationship between log X_1 and log Y may be linear. Plots of all X's versus Y should be prepared to permit visual examination of the relationships. Also, the physical nature of the problem may suggest an underlying relationship between Y and X_i.

2. Find a nonlinear functional form through the use of polynomial regression. The form of the model is

$$Y = a_0 + a_1 X + a_2 X^2 + \ldots + a_n X^n \qquad (2)$$

The number of curves in the regression line depends on the degree of the polynomial (or highest exponent of X). The number of curves is always one less than the degree of the model.

3. Introduce interaction (or product) terms as additional variables.

The assumption in linear regression is that the effect of an X_i variable on Y is the same across all values of other X's. This means, for example, that the effect of asphalt surface thickness on the occurrence of alligator cracking is the same regardless of the level of other variables such as traffic, climate, or subgrade. If, however, the effect of asphalt surface thickness on the occurrence of alligator cracking is much different depending on whether the pavement is located in a warm or a cold climate, then an interaction exists between surface thickness and climate. The usual method of handling the problem of interaction is to use product terms of the two or more variables that interact (e.g., X_1X_2). Thus, a new variable X_1X_2 is created that is a function of both X_1 and X_2. The resulting equation is then

$$\hat{Y} = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_1 X_2 \qquad (3)$$

This model includes the additive effect of X_1 and X_2 and the interaction term X_1X_2, which represents the combined effect of X_1 and X_2 over and above the sum of a_1X_1 and a_2X_2. When more X's are involved, more interactive terms should be studied.

Boundary Conditions

The model should meet the boundary conditions that the physical situation requires. For example, when traffic-load-associated distress is being predicted, the distress prediction should be zero when no traffic loads have been applied. If PSI is predicted, the model should be capable of computing realistic values at the beginning and end of the pavement's life cycle.

Sensitivity Analysis

A sensitivity analysis shows the relative influence of changes in the independent variables on the dependent variable. The influence of the dependent variable (e.g., PSI or distress) can then be compared with experience or available data to see whether it is realistic. The sensitivity analysis can be conducted in various ways on the prediction model, but it should (a) be limited to the range of the variables used to derive the model and (b) consider the interrelationship of the variables. It should be noted that the least-squares regression coefficients are adjusted for other variables in the model. When the X variables are highly correlated, the individual coefficients do not provide an independent assessment of the effect of the variable on performance. Thus, it would be incorrect to vary only one variable (X) at a time to determine its influence on the performance (Y). A sensitivity analysis can be conducted in this case by varying all correlated variables in a reasonable way and noting their influence on performance.

The sensitivity analysis should be able to provide information to determine the general influence of the variables on performance, particularly the sign of the coefficient (+ or -); establish the relative importance of the variables; and determine deficiencies in the model.

STATISTICAL CRITERIA

Statistical Inference

Statistical criteria can be used to assess the precision of the estimated regression model. Initially, the form of the mathematical model must be assumed (such as Equation 1) based on the best judgment of the engineer. Then, after it is derived, it must be critically examined to either verify or reject the assumption. Two commonly used testing procedures are (a) the overall test for goodness of fit of the regression model and (b) the test for a specific regression coefficient. However, the residuals, as indicated by the standard error of the estimate, provide a direct indication of the precision of the model. It must be noted that, no matter how well the model fits the experimental data, if the data base is deficient, the model will also be deficient. Thus, the statistical tests relate only to the specific data used in the model's development. Another point is that the data base represents a sample of the population of all data, and thus the regression model developed from the data-base sample is only an estimate or inference of the true regression model that would be obtained if all possible data were used.

Error of Prediction

Whenever experimental data are used to develop a regression model, there will be a scatter of data about the line, as illustrated in Figure 3. The actual data points are given as (X_1, Y_1), (X_2, Y_2), etc. The X's represent the independent variable (e.g., slab thickness) and the Y's are the dependent variable (e.g., PSI or distress). A regression model of the form

$$Y = a_0 + a_1 X \qquad (4)$$

is fitted to the data by using the least-squares technique. For a given value of X, say X_1, there is a difference between the actual value Y_1 and the predicted value $\hat{Y}_1$ obtained from Equation 2. This difference is called a residual or error in prediction: Residual = $Y_i - \hat{Y}_i$. The residuals contain all available information on the ways in which the regression model fails to explain the measured Y.

In developing a regression model from an in-service pavement data base, the variation about the regression line is caused by the following sources:

1. Test-equipment or observation-measurement repeatability errors (called testing errors),
2. Differences between the performance of supposedly identical pavement sections (called replicate errors), and
3. Model errors caused by the model having either an inadequate number of variables or an incorrect functional combination of variables.

Sources 1 and 2 of the total variation are called pure error, and source 3 is called lack-of-fit error. The pure error can be computed only if the data bank contains replicate projects having identical X values (e.g., structure, age, traffic, and climate). Any difference between replicate projects is assumed to be the result of random variation. Thus, when data collection is planned, it is important to obtain several replicate projects. Once the pure error is calculated, the degree of lack-of-fit error can be assessed, as shown in Figure 4.

The total residual sum of squares is computed as

$$SS_{res} = \Sigma(Y_i - \hat{Y}_i)^2 \qquad (5)$$

It is composed of the pure-error sum of squares and the lack-of-fit sum of squares:

$$SS_{res} = SS_{pe} + SS_{lof} \qquad (6)$$

If the mean squares attributable to pure error and lack of fit are computed, they can be compared, as shown in Figure 4. If they are significantly different, then the proposed regression model suffers from lack of fit and is inadequate, and a new model should be developed. If not, there is no reason to doubt the adequacy of the regression model (based on available data).

The standard error of the estimate (SEE) is computed as

$$SEE = \sqrt{\Sigma(Y_i - \hat{Y}_i)^2/(N - 2)} \qquad (7)$$

The magnitude of the SEE is simply the standard deviation of the residuals and may be interpreted approximately as the "average error in predicting Y from the regression model" (12). The size of the SEE can be compared with the mean of all Y's. Ideally, the SEE should be much smaller than the mean of all Y's.

The residuals $(Y_i - \hat{Y}_i)$ should be carefully examined. Various plots can be prepared, such as (a) overall plot of residuals, (b) time sequence if order is known or meaningful, (c) plot against the calculated $\hat{Y}$ values, (d) plot against the independent X variables, and (e) any way that makes sense for the model under evaluation (11).

Multiple Correlation Coefficient (R^2)

The overall accuracy of the regression model can be assessed by the multiple correlation, R^2. The total sum of squares in Y (which represents the overall variation of the performance variable Y) consists of two parts:

$$SS_y = SS_{reg} + SS_{res} \qquad (8)$$

where

$SS_y = \Sigma(Y - \bar{Y})^2$,
$SS_{reg} = \Sigma(\hat{Y} - \bar{Y})^2$, and
$SS_{res} = \Sigma(Y - \hat{Y})^2$.

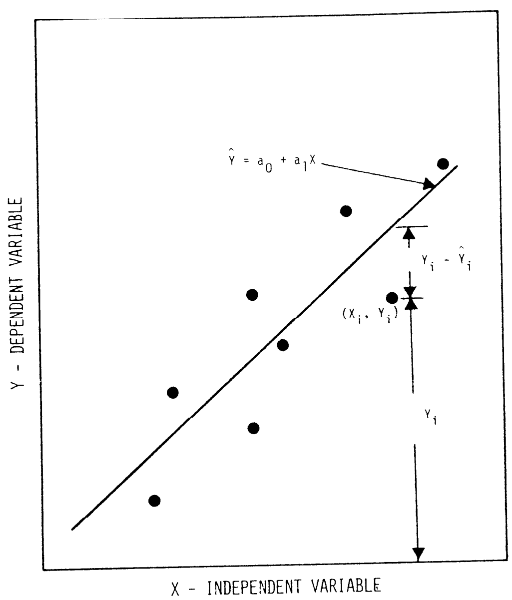
If these sources of variations are used, a natural measure of prediction accuracy is obtained, as follows:

$$R^2 = SS_y - SS_{res}/SS_y = SS_{reg}/SS_y \qquad (9)$$

Thus, the R^2 represents the proportion of the total variation in Y explained by the regression model. The closer that R^2 is to 1.0, the closer the data cases lie on the predicted line, and the closer to 0.0, the greater the scatter of data about the line.

A statistical test can be employed to test the null hypothesis that the R^2 is zero. This would indicate that there is no significant relationship between any of the X variables and the Y performance variable. It is equivalent to the null hypothesis that all a_i regression coefficients are equal to zero. Thus, if the null hypothesis is rejected, one or more of the coefficients has an absolute value greater than zero. The test does not determine which a_i value is nonzero. Thus, further tests are made on the regression coefficients, as explained later. The value of R^2 that is statistically significant at some level of significance varies greatly as the number of data cases used to develop the equation changes. The larger the data bank, the lower the R^2 needed to reject the null hypothesis (and thus accept the alternative hypothesis that correlation exists). Regression analysis with in-service pavements typically produces relatively low R^2 values because of the large variations and many unknown factors that affect performance.

Figure 3. Illustration of typical scatter of data about a linear regression line.



Regression Coefficients

The regression coefficients (a_i) represent the expected change in Y with a change in one unit in one X variable when all other X's are held constant. In the stepwise regression technique, the coefficient of each variable is tested as it enters the equation to see whether it differs significantly from zero. This test can be used (and normally is) as a criterion to decide whether or not to enter a given variable into the regression model. If the null hypothesis of $a_i = 0$ cannot be rejected, then it can be concluded that the X variable does not significantly affect the Y variable, and it should not be allowed in the regression model.

In summary, the model should meet the following statistical criteria:

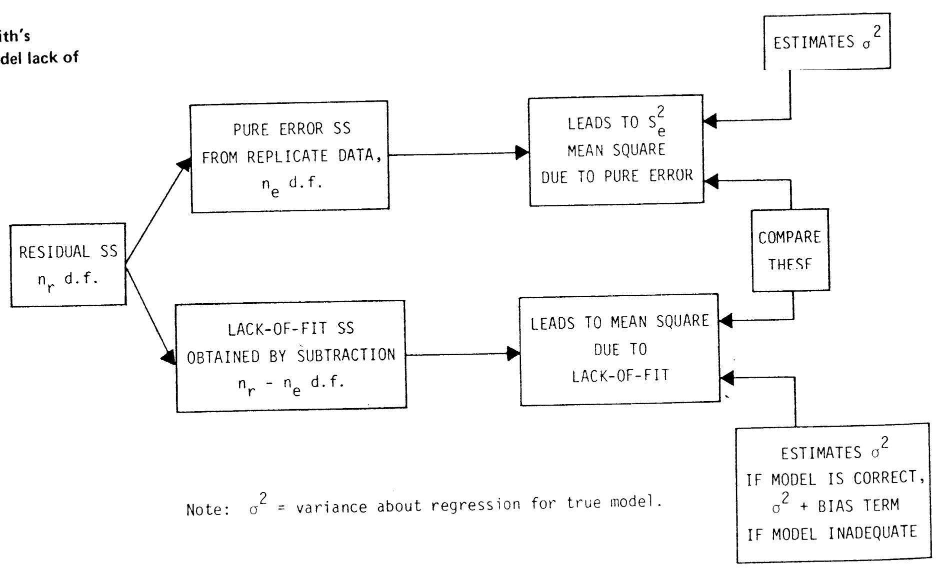
1. The final model should explain a high percentage of the total variation about regression (or R^2) to indicate the overall model accuracy;
2. The standard error of the estimate of the model should be less than a specified practical value (e.g., < 0.20 of the mean);
3. The model should not suffer from significant lack of fit;
4. All estimated coefficients of the X variables should be statistically significant with, say, $\alpha \leq 0.05$; and
5. There should be no discernible patterns in the residuals.

CONCLUSIONS

The development of and requirements for reliable models for the prediction of pavement peformance are presented.

1. An adequate data base from which to build the model is most important. Adequacy is defined in terms of having a representative unbiased sample of projects, reliable and accurate data, and a sufficient number of data cases that include some replicates.
2. The model must include all variables that have significant influence on the performance. If

Figure 4. Draper and Smith's determination (11) of model lack of fit.



it does not, the limitations of the models should be identified. Mechanistic variables such as stress, strain, or stress-and-strength ratio should be considered, since this may greatly increase the reliability of the model. The stepwise regression procedure is believed to give the best selection of independent variables.

3. The functional form of the model should be carefully selected to represent the physical real-world situation as closely as possible. This will lead to a model that considers the appropriate shape, nonlinearity, and interactions of variables; meets boundary conditions; and also gives reasonable sensitivity of the variables. Such selection requires extensive knowledge of the problem and the available data.

4. Various statistical criteria should be used to assess the precision of the model. The model should explain a high percentage of the total variation about regression; the standard error should be less than a practical value for usefulness; there should be no discernible patterns in the residuals; the model should not suffer from significant lack of fit; and all estimated coefficients should be significant with, say, $\alpha \leq 0.05$. Detailed explanation of regression-model development and testing may be found in the literature (11-15).

5. Significant progress can be made in pavement technology if agencies will begin the development of in-service pavement data bases from which reliable predictive models can be developed and used for pavement management purposes.

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Characterization of Bitumen-Treated Sand for Desert Road Construction

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This paper summarizes the findings of an experimental program designed to permit evaluation of the accumulation of permanent deformation in bitumen-treated sand layers by applying the more rational methods of pavement analysis and design. The primary part of the work consists of the characterization of the cumulative deformation response of bitumen-sand specimens tested under simulated conditions of temperature and dynamic stress. Results have been analyzed by using multiple regression analysis, and predictive relationships of rut depth are formulated therefrom.

The developing economies of many countries in the Middle East have resulted in an increasing demand