Calculation of Aggregate Pavement Condition Indices from Damage Data Using Factor Analysis

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Aggregate pavement condition indices are used by many agencies in the United States and abroad to select maintenance strategies and program network rehabilitation strategies. These indices are usually calculated as weighted sums of several individual damage measurements such as length of transverse cracks, rut depth, and roughness. Existing approaches to condition index calibration are reviewed and a statistical procedure for developing pavement condition indices from distress measurements using factor analysis is described. This method is used to reestimate a condition index from the data collected in the AASHO Road Test for calibration of the present serviceability index (PSI). The new index is compared with the PSI.

The measures used for evaluating pavement condition differ depending on the perspective of the evaluator. Different terms are used in the condition evaluation literature to reflect these perspectives. For example, the broadly defined terms "distress" or "damage" or an aggregate measure such as "condition" have been used to describe the surface quality of the pavement and to schedule maintenance based on this quality. Similarly, the term "serviceability" has been used to define the roughness or ride quality characteristics of the pavement from a user's perspective. Terms like "skid resistance" describe the pavement condition from a safety perspective. These aggregate evaluations of pavement condition are often referred to as indices.

Even though these different terms for pavement condition have been identified in the literature, there has been a tendency to use them interchangeably, and policy decisions on pavement maintenance have not adequately reflected the different characteristics measured by the different indices. However, there is an advantage in being able to precisely tie a condition index to the specific characteristic of pavement deterioration measured by the index, because maintenance decisions can then be taken to correct that characteristic. For example, if a condition index can be defined as roughness related, then this information can be used to plan strategies that improve the pavement ride quality. It is therefore desirable to develop indices that can be defined in terms of their primary deterioration characteristics rather than in terms of broad and sometimes misunderstood terminology. By doing so, it is then possible to identify the different dimension of deterioration of the pavement and to schedule maintenance to correct this deterioration. Factor analysis techniques are used herein to estimate such indices. The indices are developed from the AASHO Road Test data that were used to calibrate the familiar PSI equation. This procedure is for purposes of easy comparison with existing indices such as the PSI.

Another reason for using factor analysis as a technique is that it does away with the reliance of traditional indices on inspector judgments for their calibration, if required. Although experienced inspectors can provide valuable information on the relative condition of different pavements, it is difficult to evaluate the precision of these judgments. Models developed using these evaluations may not be as easily transferable to other locations as models developed from data collected through a standardized measurement scheme. The initial models estimated only use measured information for the calculation of the condition index; subsequent models use the inspector ratings as additional information, but these can be omitted if there is reason to believe that these ratings are inaccurate or biased. The factor analysis models are therefore not intrinsically dependent on judgments for their estimation.

The following section describes some common deterioration indices used in practice. Specifically, the calibration of the PSI equation from AASHO Road Test data and some of the problems associated with its use are discussed along with some background on methodology. The following section, which is a mathematical specification of factor analysis models, describes estimation methods. Estimation results are presented, and finally, conclusions.

PAVEMENT CONDITION INDICES: DESCRIPTION AND CALIBRATION

The basic problem with the calibration of aggregate indices for pavement condition is that it is not possible to directly measure the condition of a pavement. Although natural measurements exist for the different components of pavement damage (e.g., area cracked, rut depth, and slope variance) pavement condition itself is an unobservable (or latent variable) and as discussed in the previous section, can be defined in different ways depending on the evaluator's perspective.

Calibration of aggregate pavement indices is often performed by regressing a measure of serviceability or condition against a set of damage measurements. In order to obtain a quantitative measure for condition, experienced pavement inspectors are asked to rate the pavement on an arbitrary

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quantitative scale. The scale of measurements and the inspectors chosen may differ depending on the particular deterioration characteristics (e.g., surface quality, structural strength, or safety) that the index is intended to capture. The estimated parameters are the weights assigned to each damage measurement. After calibration, the fitted value of the index can be simply calculated from future damage measurements using the estimated weights.

In order to illustrate the form and use of aggregate indices, four examples are presented. The first and probably the most widely used in the United States is the present serviceability index (PSI). It was developed by Carey and Irick (*1*) as a means of establishing a failure condition for the AASHO Road Test in terms of the users' response to pavement condition. It is an approximation to the present serviceability rating (PSR), which is the mean value of ratings assigned to a pavement on a discrete scale from 0 to 5 (where 5 is a new pavement and 0 represents complete deterioration) by a panel of experienced raters representing highway users. The original definition is based on the following five assumptions:

1. Safe and smooth highways are desirable;
2. Users' ratings of highways are subjective;
3. Weighted, measured pavement characteristics can be developed that relate to the users' subjective evaluations;
4. Serviceability is the average of all users' evaluations; and
5. Performance is the overall serviceability history.

The third assumption is the basis for developing PSI as a mathematical combination of physical measurements of cracking, patching, rut depth, and slope variance to predict PSR. The PSI, on the basis of measured quantities, is both less expensive to obtain than the PSR and intuitively more appealing to engineers. It is used to predict performance over time and is used by the Highway Performance Monitoring System (*2*) to provide an overall evaluation of the U.S. highway system.

The second example is the pavement condition index (PCI), which was developed by the U.S. Army Corps of Engineers at the Construction Engineering Research Laboratory. For flexible pavements, the PCI is constructed from 19 different damage types and is an aggregate measure of pavement surface damage on a scale from 0 to 100. It is used in the PAVER pavement management system to identify maintenance and rehabilitation alternatives and to forecast pavement condition. This management system has been adopted by several military bases, cities, and counties.

The third example is a series of indices used in Canada. They are the visual condition index (VCI) or surface damage index, the roughness condition index (RCI), and the structural adequacy index (SAI). Each index is based on a weighted function of observations of pavement damage to give an index on a scale of 1 to 10 (*3–5*). They are aggregated into the pavement quality index. They are also used for street maintenance programming and network rehabilitation programming (*6*).

The final example is a simple distress index used in Finland (*7*). It is a weighted, linear function of the area of alligator cracking, length of longitudinal cracking, length of transverse cracking, number of holes, and area of worn surface. This index is then used to determine rehabilitation needs.

As discussed in the previous section, although trained inspectors are able to make relatively accurate assessments of the aggregate pavement condition, the introduction of a judgmental measure introduces an uncontrollable arbitrariness into the procedure for calibration. As a result, these models need to be used with caution, especially in locations different from where they were originally estimated. Carey and Irick (*1*) point this out in their discussion about the PSI concept, and the warning is subsequently reiterated by Haas and Hudson (*5*). However, because of the expense and effort of calibrating a new model for each application, these limitations have been largely ignored. The problem of transferability is magnified in this particular instance because the slope variance is now measured with a device that is calibrated differently from the type used in the AASHO Road Test (*5*).

Another problem relates to the lack of statistical information reported with the models. Because typically somewhat ad hoc measures have been used to measure and calibrate the models, information on *t*-statistics or goodness-of-fit is rarely found in the literature. Therefore, future users of the model have no knowledge of how well the model fits the data, or even if the model was properly specified. This makes the transferability of these models uncertain as well.

In order to illustrate this point, a reestimation of the basic PSI equation for flexible parameters was conducted to obtain the statistics not reported in the original literature. The data, comprising ratings and damage measurements from 74 sections in Illinois, Minnesota, and Indiana, was provided by Carey and Irick (*1*).

The functional form of the PSI equation was based on transformations of the measurement of slope variance, mean rut depth, and area of cracking and patching developed through plots of the data against PSR. The results from the reestimation using ordinary least-squared regression are as follows:

$$\mathrm{PSI} = 5.06 - 0.01\,(C + P)^{1/2} - 1.36\,\mathrm{RD}^2 - 1.96\log_{10}(1 + \mathrm{SV}) \quad (1)$$

where

$(C + P)$ = area of alligator and linear cracking and patching (ft^2);
RD^2 = square of rut depth ($\mathrm{in.}^2$); and
$\log_{10}(1 + \mathrm{SV})$ = log of slope variance to base 10 ($\times 10^6$).

The *t*-statistics for the coefficients are 37.73, −0.84, −3.88, and −13.21 and the R^2 value is 0.83. The coefficients in Equation 1 are the same as those developed by Carey and Irick (*1*) except for the second decimal place. The differences are probably caused by rounding errors. Although the fit is good, the *t*-statistics indicate that the cracking and patching term is not significant. As also noted (*8,9*), the main emphasis is on roughness measured in terms of slope variance. However, despite the lack of significance of some of the dependent variables, this model has been widely used.

The factor analysis methodology, described in detail in the following section, seeks to address some of the issues mentioned in this section. The procedure, as mentioned before, does not need inspector ratings for calibration, though this can be included as additional information. Also, the goodness-of-the-information is used to determine the extent to which

each measurement contributes to the calibration of the performance index. This provides an analytical basis for distinguishing between different indices.

FACTOR ANALYSIS: AN OVERVIEW

A factor analysis model describes the covariance relationships among many variables in terms of a few underlying, but unobservable random quantities called factors (*10*). Factor analysis models have been widely used in psychometrics for extracting unobservable measures of quantities such as verbal or analytical ability from standardized test scores. More recently, it has been used in engineering applications for identifying uncorrelated pavement distress categories for pavement design and long-range planning (*11*), and to determine true distress from measurements made by a set of different inspection technologies (*12*).

Suppose there exist some observed variables that are grouped by their correlations. Then all variables that are highly correlated with each other but are not highly correlated with members of other groups can be thought of as measuring a single underlying variable. A factor analysis model is a parametric construct of this concept, and the parameter estimates indicate the extent to which the measured variables represent the unobserved factors. From the earlier discussion, it is clear that the problem of extracting a performance index from several damage measures can be modeled using the factor analysis approach. The performance index is the underlying unobserved factor, and can be represented by a group of damage measurements. The formal specification is now presented.

Specification of a Factor Analysis Model for Highway Pavements

For purposes of illustration, a single latent factor S is assumed to be represented by three measurements of damage, I_1, I_2, and I_3. Clearly, it is possible to have more than one unobserved factor represented by the same set of measurements. The specification assumes that each observed variable can be expressed as a linear function of the latent factor plus an error term. In algebraic terms, this can be written as

$$I_1 = \lambda_1 S + \varepsilon_1 \tag{2a}$$

$$I_2 = \lambda_2 S + \varepsilon_2 \tag{2b}$$

$$I_3 = \lambda_3 S + \varepsilon_3 \tag{2c}$$

where

I_1, I_2, and I_3 = measurements of damage,
S = unknown factor,
λ_1, λ_2, and λ_3 = factor loadings, and
ε_1, ε_2, and ε_3 = error terms.

The factor loadings reflect the extent to which each measured variable represents the latent factor. This can be seen by examining the variance of the observed variables of Equation 2. Considering the first of the three equations, for example,

$$\text{Var}(I_1) = \lambda_1^2 \text{Var}(S) + \text{Var}(\varepsilon_1) \tag{3}$$

Equation 3 partitions the variance of the observed measurement into two parts: the variance of the latent factor multiplied by λ_1^2 and the variance of the error term. Analogous to a regression equation, a goodness of fit statistic for Equation 3 is the ratio of explained variance [that is, λ_1^2 Var (S)] to the variance of I_1. As λ_1 increases in magnitude, the explained variance term increases and the corresponding measurement plays a greater part in explaining the latent factor.

Estimation of the Parameters of the Factor Analysis Model

The parameters λ_1, λ_2, and λ_3 of Equation 2 are estimated by comparing the observed covariance matrix of the measured variables with a calculated covariance matrix expressed as a function of the parameters. To illustrate this, consider Equations 2a and 2b. Assuming S and ε are independent, the covariance between I_1 and I_2 can be calculated as follows:

$$\begin{aligned}\text{Cov}(I_1, I_2) &= \text{Cov}[(\lambda_1 S + \varepsilon_1)(\lambda_2 S + \varepsilon_2)] \\ &= \lambda_1\lambda_2 \text{Var}(S) + \text{Cov}(\varepsilon_1, \varepsilon_2)\end{aligned} \tag{4}$$

If the variance of the latent factor is denoted by ψ, and the error term covariance by θ_{12}, then Equation 4 can be written as

$$\text{Cov}(I_1, I_2) = \lambda_1\lambda_2\psi + \theta_{12} \tag{5}$$

Comparing Equation 5 with the observed covariance between I_1 and I_2 calculated from the sample data provides an equation in terms of λ_1, λ_2, ψ, and θ. Similar equations can be written for six observed variances and covariances between I_1, I_2, and I_3. Obviously, only six parameters can be estimated from these equations; the others have to be set to zero. The choice of which variables to set to zero depends on the assumptions made from a priori knowledge about the independence of error terms in the model specification; for example, in Equation 5, if there is no reason to believe that the measurement errors of I_1 and I_2 are correlated, then θ_{12} can be set to zero.

In addition to setting all but six parameters to zero, one parameter for each factor has to be fixed to set the scale of the model. From Equation 5, it can be seen that for any nonzero constant M, $\lambda_1 M$ and $\lambda_2 M$ will satisfy the equation as well as λ_1 and λ_2. There are therefore infinite solutions to the factor analysis problem unless one of the parameters is fixed. Typically, one of the λs (for example, λ_1) is set to a fixed value of 1. The other parameters are then calculated relative to this value.

In practice, the parameters are estimated by an iterative least-squares-like procedure that minimizes the weighted squared distance between the observed and calculated covariance matrices. If the observed covariance matrix is denoted

by **V** and the calculated covariance matrix by Σ, then the objective function F to be minimized is given by

$$F = [(\mathbf{V} - \mathbf{\Sigma})' \mathbf{W}^{-1}(\mathbf{V} - \mathbf{\Sigma})] \tag{6}$$

where

V = observed covariance matrix of the parameters,
$\mathbf{\Sigma}$ = calculated covariance matrix, and
W = a matrix of weights.

The estimator is called the "asymptotic distribution free" (ADF) estimator and produces consistent estimates irrespective of the sampling distribution of I. If **W** is set to be an estimate of the covariance matrix of **V** (that is, products of second and fourth order terms in I), then the estimates produced are also best in the sense of having minimum variance. Further details on factor analysis models and the estimation procedure have been provided elsewhere (*10,13,14*).

Extraction of Factor Scores

Estimation of the parameters of Equation 2 does not produce a value for the latent factor S. This value is obtained by an ad hoc regression-like procedure after the parameters have been estimated. In order to compare the factor analysis procedure with an existing model such as the PSI model, it is necessary to express the factor S in terms of its associated measurements **I**. Such a model can be specified as follows:

$$S = \boldsymbol{\alpha}\mathbf{I} + \nu \tag{7}$$

where $\boldsymbol{\alpha}$ is a vector of parameters, and ν is an error term.

Equation 7 looks like a regression model, and so an expression for $\boldsymbol{\alpha}$ can be written analogous to a traditional least squares estimator as follows:

$$\boldsymbol{\alpha} = \text{Var}\,(\mathbf{I})^{-1}\,\text{Cov}\,(\mathbf{I},S) \tag{8}$$

For each observation (or pavement section), given a vector of damage **I**, the value of S can now be calculated from Equation 7. This is the value of the latent pavement condition for that section. The variance and covariance terms of Equation 2 can be calculated after the parameters have been estimated from equations such as Equation 5. Further detail on the extraction procedure has been provided elsewhere (*15*).

MODEL RESULTS

In order to compare the factor analysis model results with the PSI equation, the first specification given by Equation 1 (referred to as MODEL1) uses the same measurements as the PSI [that is, $(C + P)^{1/2}$, RD^2 and $\log_{10}(1 + SV)$] as determinants of the unknown factor S_1. Comparison of this model with the PSI indicates that the factor S_1 is in fact slightly different from the PSI. The second specification given in Equation 13 and referred to as MODEL2, is an attempt to produce a PSI-like factor; this is done by adding the PSR as an additional measurement to the specification of MODEL1. The factor S_2 produced from this model is highly correlated with the PSI. The fact that two different factors, S_1 and S_2, can be extracted from the data indicates that a two-factor specification is a more appropriate model. This specification, called MODEL3, is given in Equation 15.

MODEL1: Factor Analysis Model with PSI Measurements

The specification of MODEL1 is as follows:

$$\begin{aligned} I_{CP} &= \lambda_{CP}S_1 + \varepsilon_{CP} \\ I_{RD} &= \lambda_{RD}S_1 + \varepsilon_{RD} \\ I_{SV} &= \lambda_{SV}S_1 + \varepsilon_{SV} \end{aligned} \tag{9}$$

where

I_{CP}, I_{RD}, I_{SV} = measurements for $(C + P)^{1/2}$, RD^2 and $\log_{10}(1 + SV)$, respectively;
S_1 = unknown factor;
λ_{CP}, λ_{RD}, and λ_{SV} = parameters to be estimated, and
ε_{CP}, ε_{RD} and ε_{SV} = error terms.

Computational requirements necessitate a transformation of the measurements so that the diagonal elements of the observed covariance matrix **V** are all of the same magnitude. The following transformations are used in this specification of MODEL1:

$$\begin{aligned} I_{SV} &= \log_{10}(1 + SV) * (10.0)^{1/2} \\ I_{RD} &= RD^2 * 10 \\ I_{CP} &= (C + P)^{0.5}/10.0 \end{aligned} \tag{10}$$

The parameter estimates are presented in Table 1. As discussed in the previous section, one of the parameters needs to be fixed to set the scale for the model. In Table 1, λ_{SV} is set to 1, and the other parameters are estimated relative to this fixed value.

There is no single standard method that can be used to interpret the parameter estimates of Table 1. The magnitudes of the parameters are not meaningful because they are dependent on the scale of the individual measurements. Similarly, the reported t-statistic can only be used as a broad guideline for statistical significance if the data come from a distribution that is Kurtose, because the distribution of the parameter estimates is unknown in this case (*14*). The signs of the parameter estimates and the fit of each equation, reported in

TABLE 1 PARAMETER ESTIMATES FOR MODEL1

Parameter	Estimate (t-statistic)	R^2
λ_{SV}	1.00 (-)	0.58
λ_{RD}	-0.07 (-0.51)	0.003
λ_{CP}	0.70 (0.97)	0.72

Table 1 as the R^2 value, provide insight into the nature of the unknown factor S_1. The sign of the rut depth parameter is negative, indicating that the pavement improves in the dimension of S_1 as the rut depth increases. However, the low t-statistic and negligible fit imply no contribution of the rut depth measurement to S_1. The best fit is obtained for the cracking equation, indicating that the factor S_1 probably describes some underlying index that is a mixture of cracking and slope variance with an emphasis on cracking. In this way, it differs from the PSI, which places emphasis on the slope variance.

This difference between S_1 and the PSI can also be seen when the factor is expressed as a function of the damage components in an equation similar to the PSI relationship using the extraction method described in Section 3. The positive signs of λ_{CP} and λ_{SV} imply that as the measurements I_{CP} and I_{SV} increase, the value of S_1 increases. In other words, increasing values of S_1 reflect decreasing condition of the pavement. Because this is opposite to the direction of the PSI, the negative PSI (referred to as $-$PSI) is used for comparison.

The PSI equation (Equation 1) also needs to be transformed so that the variables in both the PSI and the factor equation have the same scale. When this is done, the following equations are obtained:

$$-\hat{\text{PSI}} = I_{SV} + 0.22I_{RD} + 0.11I_{CP} \tag{11}$$

$$\hat{S}_1 = I_{SV} - 0.04I_{RD} + 3.26I_{CP} \tag{12}$$

where $-\hat{\text{PSI}}$ and $\hat{S}_1$ represent the fitted values and the other variables have been defined before. As is evident from these equations, the ratio of the slope variance coefficient to the cracking coefficient is approximately 10 in Equation 11 and is 0.3 in Equation 12. This indicates that the PSI equation places a greater relative importance on the slope variance measurement than the latent factor equation.

This difference is also shown in Figure 1, which is a scatter plot of $-\hat{\text{PSI}}$ against $\hat{S}_1$. For good-condition pavements, there is relatively close correlation, probably because pavements in good condition have low cracking and low roughness. For more deteriorated pavements, a higher degree of scatter is observed.

Factor analysis of the PSI measurements therefore produce a factor reflecting different underlying characteristics than the PSI. S_1 has more to do with the structural strength of the pavement than with the ride quality. In order to estimate a roughness-related factor, the pavement rating, PSR, is included in the model as an additional measurement. This specification, called MODEL2, is now described.

MODEL2: Factor Analysis Model Including PSR

The use of rating information such as PSR is valuable as it reflects engineering judgment and field experience. This information has been integrated into the second model. The specification of MODEL2 is similar to that of MODEL1, except for an additional measurement equation for the PSR. The complete specification can be written as follows:

$$\begin{aligned} I_{CP} &= \lambda_{CP}S_2 + \varepsilon_{CP} \\ I_{RD} &= \lambda_{RD}S_2 + \varepsilon_{RD} \\ I_{SV} &= \lambda_{SV}S_2 + \varepsilon_{SV} \\ I_{PSR} &= \lambda_{PSR}S_2 + \varepsilon_{PSR} \end{aligned} \tag{13}$$

where

I_{PSR} = measurements for PSR,
S_2 = unknown factor,
λ_{CP}, λ_{RD}, λ_{SV}, and λ_{PSR} = parameters to be estimated, and
ε_{CP}, ε_{RD}, ε_{SV}, and ε_{PSR} = error terms.

The parameter estimates obtained for this model are presented in Table 2.

From Table 2, it can be seen that the factor S_2 places an emphasis on the roughness-related measurements. This is evident from the fit of the slope variance and PSR equations. Rut depth has no effect on S_2 whereas the cracking and patching has a smaller, less significant effect. S_2 can therefore be referred to as a ride-quality-related factor.

S_2 can be expressed as a function of its constituent measurements.

$$\hat{S}_2 = I_{SV} - 0.005I_{RD} + 0.034I_{CP} + 0.17I_{PSR} \tag{14}$$

It is evident from this equation that the rut depth and cracking terms are less significant than the roughness terms (compare with Equation 12). $\hat{S}_2$ is more similar to the PSI (compare with Equation 11) than $\hat{S}_1$. This similarity can also be seen from the scatter plot of Figure 2 that plots the fitted value of PSI against $\hat{S}_2$. Compared with Figure 1, Figure 2 shows a much tighter relationship.

MODEL1 and MODEL2 have identified the presence of two underlying factors: (a) a structure-related factor that is measured largely by the extent of cracking, and (b) a ride-quality-related factor that is measured by the extent of pavement roughness. Even though the two factors have different emphases, they are highly correlated with a correlation coefficient of 0.85. The high correlation is understandable, because in general poor ride quality (or high roughness) is accompanied by a high level of cracking and vice versa.

In order to make the factor from MODEL2 more comparable to the PSI, the PSR term in Equation 14 was dropped and a modified factor was calculated that used the same measurements as the PSI:

$$\hat{S}_{2x} = I_{SV} - 0.005I_{RD} + 0.034I_{CP} \tag{15}$$

Figure 3 is a scatter plot of the modified factor $\hat{S}_{2x}$ and the fitted value of $-$PSI. Similar to Figure 2, the plot shows a much smaller degree of scatter than Figure 1. The latent variable of MODEL2 is therefore much closer to the deterioration characteristic represented by the PSI.

The analysis of MODEL1 and MODEL2 indicates that a more realistic specification should include both factors in the same model. This leads to a specification of a two-factor model, MODEL3, which is described in the following section.

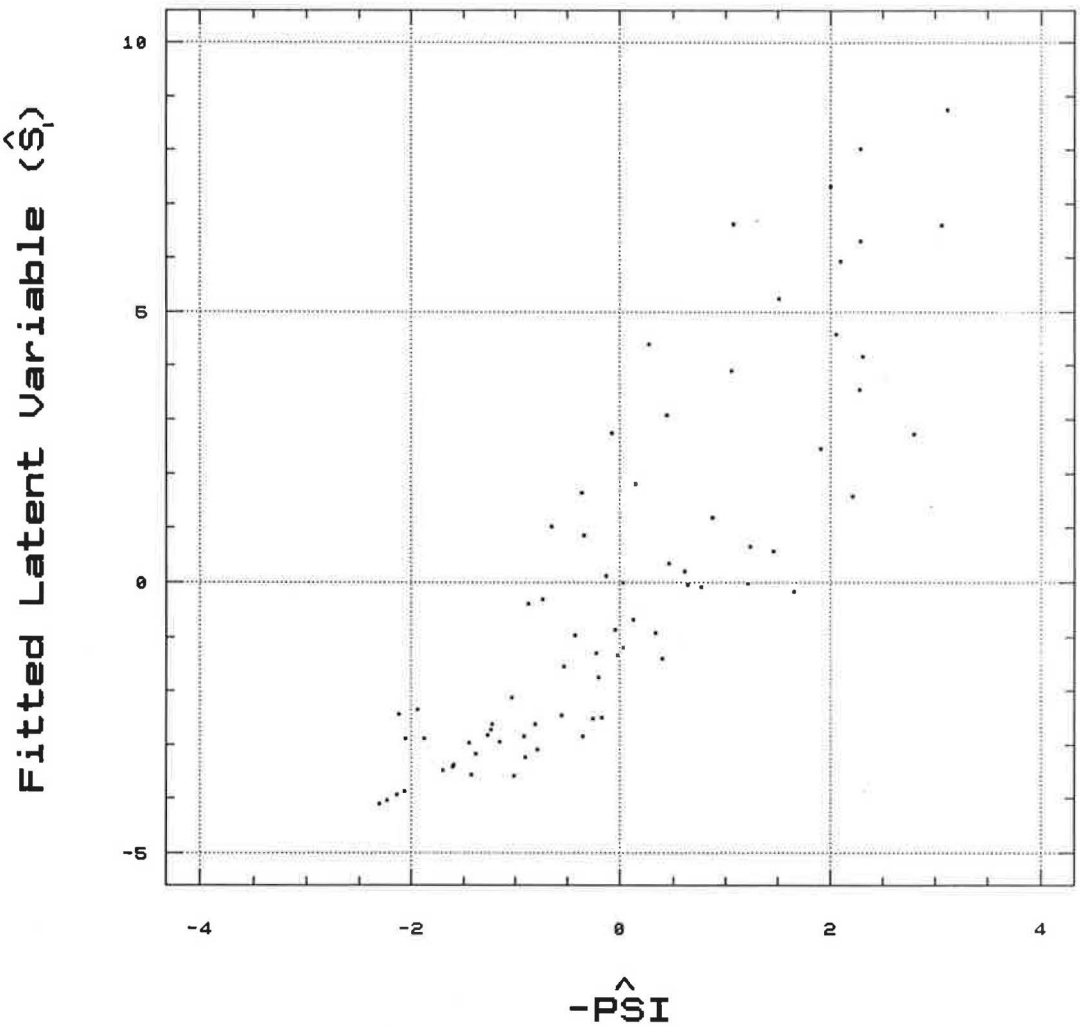

FIGURE 1 Scatter plot of $\hat{S}_1$ versus $-\hat{PSI}$ for cracking-related factor.

TABLE 2 PARAMETER ESTIMATES FOR MODEL2

Parameter	Estimate (t-statistic)	R^2
λ_{SV}	1.00 (-)	0.98
λ_{RD}	-0.05 (-0.62)	0.01
λ_{CP}	0.36 (6.01)	0.36
λ_{PSR}	0.67 (9.61)	0.85

MODEL3: The Two-Factor Model

The specification of the two-factor model differs slightly from the specification of the one-factor models described in the previous sections. In addition to the difference in specification, this model is not directly comparable to the PSI or the latent variables S_1 and S_2 because the measurements are different as well. Because the rut depth measurement did not contribute to either latent variable, it was dropped from consideration. Instead, the rut depth variance, which is a measurement available in the original road test data set, was used. The rut depth variance divided by $10^{1/2}$ is referred to as I_{RV}.

In the two-factor model, a roughness-related factor S_{31} and a cracking-related factor S_{32} are specified. The slope variance and PSR are assumed to be measurements for S_{31} and the rut depth variance and cracking and patching are assumed to be the measurements for S_{32}. The specification is as follows:

$$
\begin{aligned}
I_{SV} &= \lambda_{SV1} S_{31} + \varepsilon_{SV} \\
I_{RV} &= \lambda_{RV1} S_{32} + \varepsilon_{RV} \\
I_{CP} &= \lambda_{CP2} S_{32} + \varepsilon_{CP} \\
I_{PSR} &= \lambda_{PSR1} S_{31} + \varepsilon_{PSR}
\end{aligned}
\tag{16}
$$

In Equation 16, it is assumed that the cracking and rut depth measurements only affect the cracking-related latent variable, whereas the slope variance and PSR measurements affect only the roughness-related latent variable. However, the two latent variables themselves may not be independent,

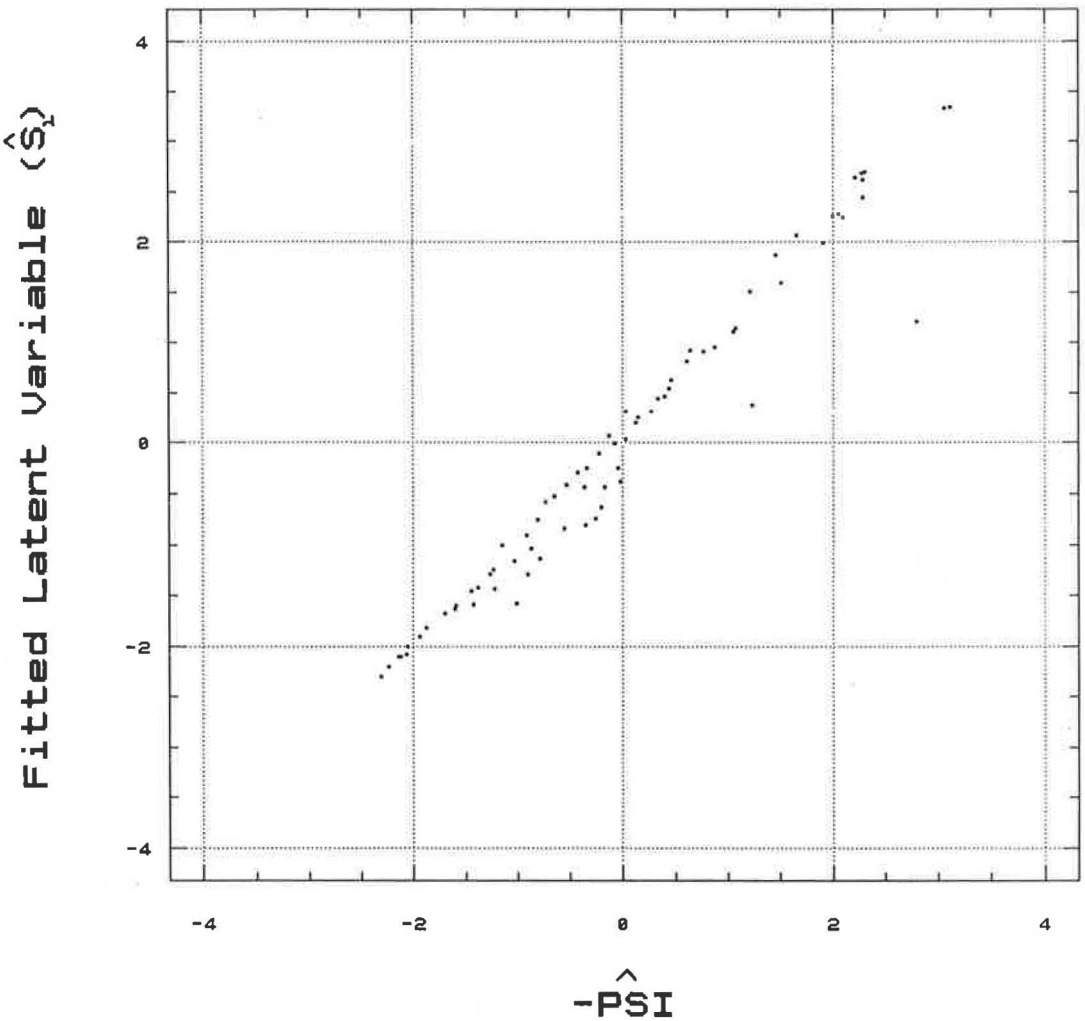

FIGURE 2 Scatter plot of $\hat{S}_2$ versus $-\hat{PSI}$ for roughness-related factor.

because the onset of cracking affects the pavement ride quality. It is therefore assumed that correlations exist between S_{31} and S_{32}. The measurements of slope variance, cracking, and rut depth are made by different instruments, so the measurement error terms are assumed to be uncorrelated. In order to set the model scale, λ_{SV1} and λ_{CP2} are set to 1. The model results are presented in Table 3.

Obviously, other assumptions about the model structure give rise to other specifications. Several alternate model specifications of MODEL3 were tested as part of this study. For the purposes of illustration, only the simplest meaningful specification has been presented here.

All the estimates in Table 3 have the expected sign and are significant. The fit of the two roughness measurement equations is high and the fit of the cracking and rut depth equations is moderate, but higher than the values obtained in MODEL2. These results indicate that the two-factor model describes the Road Test data better than either of the one-factor models.

Implications for Setting Maintenance Priorities

A practical test for the difference between the PSI and the latent variables of MODEL1 and MODEL2 is to study how these indices differ in the assignment of priority lists for maintenance. This can be measured by ranking each of the indices and testing whether the ranking sequence is the same under all the indices. The Spearman's rank order correlation coefficient is a statistic that measures the closeness between two ranked lists. A value of 1.0 indicates that the ranking is identical; values closer to 0 indicate increasing randomness.

The rank order correlation between $-\hat{PSI}$ and $\hat{S}_1$ was 0.88, whereas that between $-\hat{PSI}$ and $\hat{S}_2$ was 0.98. This indicates that $\hat{S}_2$ and the PSI produce almost identical rankings, and S_1 is fairly close as well. The picture changes somewhat when only the poorer pavements are considered. For pavements with $-\hat{PSI}$ greater than 0 (see Figure 1) the correlation with $\hat{S}_1$ dropped to 0.67, whereas the correlation with $\hat{S}_2$ was 0.90. This indicates that as the pavement condition decreases, ranking pavements for maintenance by different criteria may give rise to different maintenance priorities. It is important to consider this while making maintenance decisions.

CONCLUSION

The traditional PSI equation, of the form presented in Equation 1, has been in use for 30 years. Alternate methods for

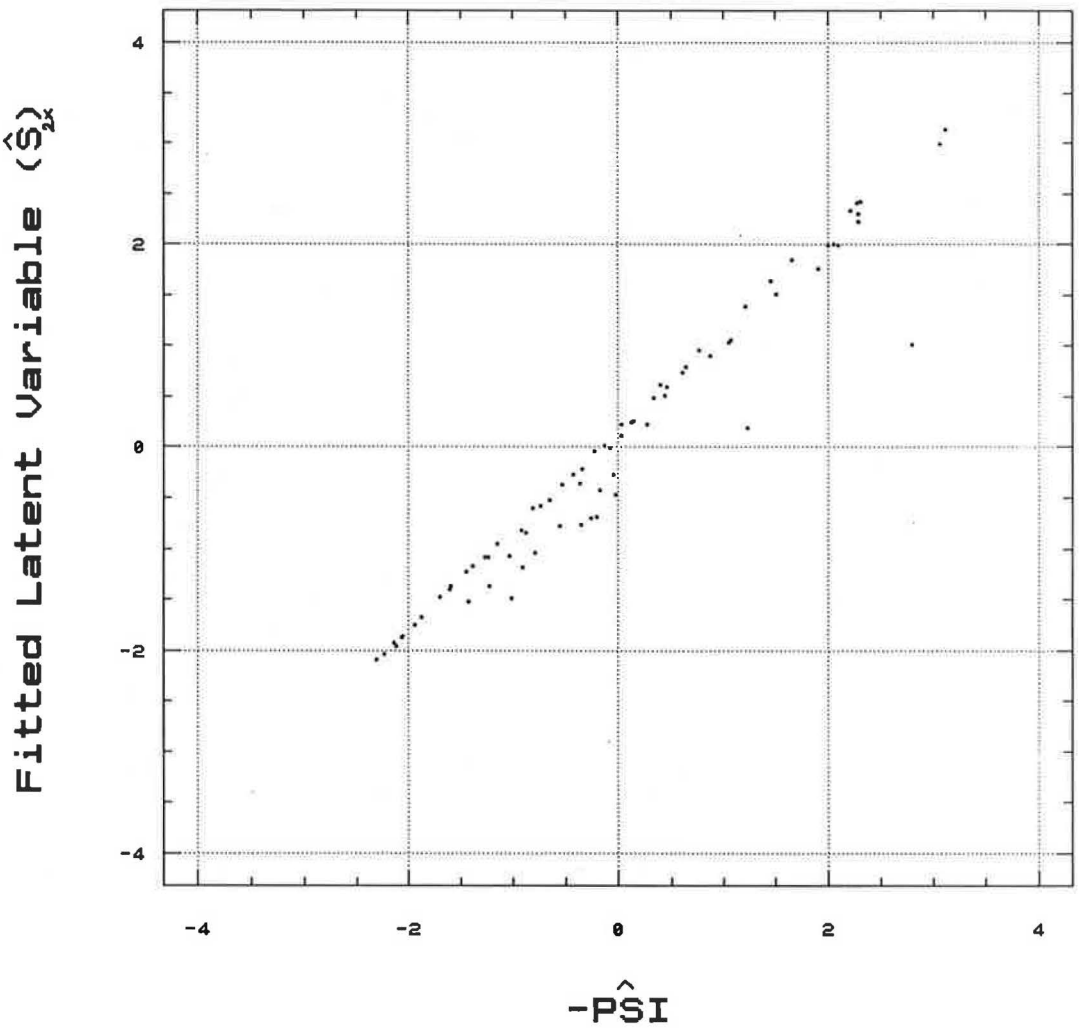

FIGURE 3 Scatter plot of $\hat{S}_{2x}$ versus $-\hat{PSI}$ for $\hat{S}_2$ without PSR measurement.

TABLE 3 ESTIMATION RESULTS FOR MODEL3

Parameter	Estimate (t-statistic)	R^2
λ_{SV1}	1.00 (-)	0.88
λ_{RD2}	1.16 (3.88)	0.54
λ_{CP2}	1.00 (-)	0.41
λ_{PSR1}	0.75 (17.95)	0.92

analyzing the data can be used to calibrate the PSI equation. Rather than specifying an a priori model linking the PSR to the damage components, the factor analysis method examines the correlations between the measured damage components. From this kind of analysis, it appears that these measurements by themselves are more highly correlated with a cracking-type performance variable rather than with a roughness-type index such as the PSI. In order to produce a PSI-like index, the PSR data were included in the measurement set. The existence of two different underlying deterioration characteristics indicates that merely substituting measured values of damage into the traditional PSI equation and using the PSI as the sole determinant of pavement condition for scheduling maintenance activities may not be accurate. This is not to say that the PSI equation is incorrect and should not be used. The roughness-related factors of MODEL1 and MODEL2 are highly correlated with the PSI, and so the PSI is a good measure of the ride quality characteristics of the pavement. However, other factors related to cracking or structural strength can also be identified in the data, and maintenance activities need to be performed to correct these aspects of deterioration as well, especially for pavements in worse condition. It has been

reported before in the pavement deterioration literature that it is necessary to use multiple performance indices to capture all aspects of deterioration, but since the different indices were calibrated differently, often with different data, there was no analytical basis for determining exactly which indices address which deterioration characteristics, and consequently how many indices form a sufficient set. The methodology presented allows for this determination.

Some additional research is required in several areas. First, in the area of multiple factor models other specifications should be explored. Also, if an index of this type is adopted, additional research is required to relate the value of the index to maintenance and rehabilitation activities. However, it appears that the use of the factor analysis methodology has the potential for producing condition indices that provide valuable information to practitioners in the field.

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