Deterioration Prediction Modeling of Virginia's Interstate Highway System

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The development of deterioration models for Virginia's Interstate pavements with 7 years of distress data is described. Roadway sections were categorized by pavement type and geographic location, and stepwise regression was used to select the significant predictors of deterioration. Different model forms were examined in an attempt to identify the most appropriate one for fitting the data. The models were evaluated by checking their goodness-of-fit statistics and conducting a series of sensitivity analyses. To further assess the models' accuracy, their predictions were compared against field-observed values. An analysis-of-variance (ANOVA) test was also conducted to compare the accuracies of two model forms and two model adjustment procedures. In general, the developed models provided an adequate fit and generated predictions that conform with accepted engineering judgment. Comparisons with field observations showed their accuracies to be quite reasonable, even for long-range predictions. Finally, the ANOVA results indicated that no significant differences existed between the two model forms tested or between the two adjustment procedures. Although the focus of the research was on developing models for Virginia, the concepts of the study are applicable to any deterioration model development effort.

Deterioration prediction models greatly enhance the capabilities of a pavement management system. Among other benefits these models allow agencies to predict the timing for maintenance or rehabilitation activities and estimate the long-range funding requirements for preserving the pavement system. In Virginia a pavement prediction model was developed by McGhee (*1*) in 1984 from data collected on I-81. McGhee's model, however, was developed when the Virginia Department of Transportation's (VDOT's) pavement management system was still evolving and condition data were limited. The annual condition surveys conducted since that model was developed have compiled a substantial amount of condition data, making more refined models possible.

PURPOSE AND SCOPE

An earlier phase of the present study constructed a screened data base that can support the modeling effort (*2*). The data base was then used to develop prediction models for Virginia's Interstate system. Specifically, the study had the following objectives:

1. To identify the major factors affecting the condition of Virginia's pavements,
2. To experiment with various model forms and identify the most appropriate one for Virginia's data, and
3. To compare the precision of the developed models and assess the accuracy of the overall prediction process.

This paper starts by describing the modeling approach adopted by the study. Following the identification of the significant predictors, both power and sigmoidal models were developed and evaluated. Finally, the models' prediction accuracy was assessed.

MODELING APPROACH FORMULATION

Categorization Scheme

The first step in formulating a modeling approach was to identify a suitable classification scheme that would yield categories with an adequate number of datum points per group. On the basis of an examination of the available data, the following sectioning scheme was adopted.

Sections were first classified according to their pavement types into (a) overlaid flexible pavements, (b) flexible pavements with no overlay, (c) composite pavements with one overlay, and (d) composite pavements with more than one overlay. Overlaid flexible pavement sections were then subdivided by district to give a separate model for each district. This controlled the variability arising from the fact that each district had its own rating team. Since the number of points available was not adequate to develop a district-specific model for the other three pavement type categories, sections were classified by geographic regions, which combine a number of contiguous districts together.

The categorization scheme (Figure 1) resulted in a total of 10 groups, since not all districts had the four pavement types within their boundaries. This scheme allowed the modeling process to capture differences in the deterioration trends of the various pavement types, as well as variations in environmental conditions and paving materials (geologic difference) between locations.

Response and Explanatory Variables

When the study was conducted VDOT's basic measure of pavement condition was the distress maintenance rating (DMR) score, which is a composite index reflecting the severity and frequency of the observed distresses in the pavement surface. Consequently, DMR represented the response variable for the models, and the next step was to identify the potential explanatory variables that were expected to have an effect on DMR. The identified potential predictors could be divided into continuous and discrete (categorical) variables.

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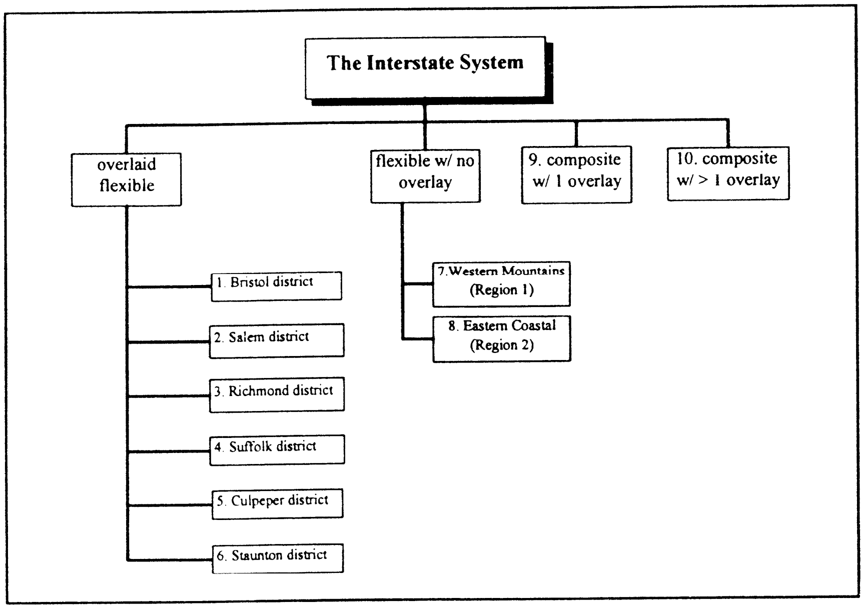

* Region one includes Bristol, Salem and Staunton districts;

** Region Two encompasses Richmond, Suffolk and Fredricksburg districts.

FIGURE 1 Classification scheme.

Continuous Explanatory Variables

The variables to be used depended on the pavement category, as will be explained. For overlaid flexible pavements the following four variables were identified:

1. AGE, the pavement age (in years) since last overlay;
2. DEPTH, the thickness of the last overlay [in cm (in.)];
3. STRNO, the structural number of the underlying pavement structure; and
4. YESAL, the average yearly equivalent single axle loads [in millions of equivalent single axle loads (ESALs)].

The YESALs were computed by dividing the cumulative ESALs to which a section has been subjected from the time of its construction to its rating date by section AGE. YESALs were used instead of cumulative ESALs to avoid multicollinearity problems arising from the very high correlation between cumulative ESALs and section AGE.

For flexible pavements with no overlay the variables were reduced to (a) AGE, (b) STRNO, and (c) YESAL. For composite pavements with either one or more overlays, the predictors were (a) AGE, (b) DEPTH (which in this case equaled the total thickness of the last asphalt concrete overlay), and (c) YESAL.

The problem, however, was that because of missing layer data (2), DEPTH and STRNO variables were not available for all records. This problem was especially evident in the overlaid flexible pavement category with respect to the structural number (STRNO) variable. Thus, STRNO was not used as an explanatory variable if its use resulted in a drastic reduction in the number of points available for modeling. It should be noted that the unavailability of such an important variable inhibits the development of theory-based models.

Categorical Explanatory Variables

Capturing the effect of categorical variables on the DMR score required the use of dummy variables, which assume only two values, usually a 1 and a 0 for linear models or 2.7183 and 1 for nonlinear models. Four groups of dummy variables were needed, as follows.

1. Dummy variables to identify the lane being rated. According to VDOT's rating practice, the lanes of the roadway section pertaining to a particular direction are rated as one unit unless their construction histories were significantly different. Since the deterioration trend of the different lanes should vary according to the truck traffic level to which they are subjected, points were divided into two groups, and a dummy variable, LANNO, was encoded as follows: LANNO was equal to 0 if the rating was performed on the whole section or on the traffic (outer) lane and was equal to 1 if any other inner lane was rated. The two cases of rating the section as a whole or rating the traffic lane were grouped together, because even when the whole section is rated, the rater is still required to emphasize the distresses observed in the traffic lane.

2. Dummy variables for the number of lanes available in each direction. To include this effect in the models, sections were divided into three groups: (a) one-lane sections, (b) two-lane sections, and (c) sections with three or more lanes. Two dummy variables, RDTYP1 and RDTYP2, were then encoded to account for these levels.

3. Dummy variables to distinguish between the individual routes within a group. To capture some characteristics specific to a particular route, ROUTID dummy variables were used to identify points belonging to the different routes within a district. The number of dummy variables equaled the number of routes within a district minus one.

4. Dummy variables to identify individual districts within a geographic region. Finally, for the cases in which classification was based on geographic region rather than individual districts, dummy variables, DISTR "No," were used to identify points belonging to the individual districts within the region.

Two main reasons favored the use of dummy variables (as in the case of the LANNO and RDTYP variables) to account for factors that might have been captured by using traffic lane distribution factors. First, the dummy variables will capture these effects even if ESAL data are missing (which is often the case). Second, the lane distribution factors are not precisely known, and the use of default values may obscure or distort the ESAL role in prediction.

IDENTIFYING SIGNIFICANT PREDICTORS AFFECTING DETERIORATION

The next task was to select from among the potential explanatory variables a subset of significant predictors to be included in the models. To this end stepwise regression was performed on each of the 10 categories by assuming a linear model of the form

$$\begin{aligned} DMR = {} & a_0 + a_1 \cdot (AGE) + a_2 \cdot (DEPTH) + a_3 \cdot (STRNO) \\ & + a_4 \cdot (YESAL) + a_5 \cdot (LANNO) + a_6 \cdot (RDTYP) \\ & + a_7 \cdot (ROUTID) + a_8 \cdot (DISTR) + \text{ error} \end{aligned} \tag{1}$$

where $a_0 \ldots a_8$ are regression coefficients.

The Statistical Package for the Social Sciences was used for the stepwise regression analysis (*3*). The procedure in this package uses a combination of forward selection and backward elimination for variable selection. For forward selection a variable enters the model if the probability associated with the F-test for the hypothesis that its coefficient is 0 is less than or equal to 0.05. In backward elimination the variable remains in the equation as long as the probability associated with an F-to-remove test does not exceed 0.10. Table 1 shows the predictor variables included in each group's model. These variables are discussed in the following sections.

AGE

AGE was included in all 10 models and was consistently found to be the variable exhibiting the highest correlation with DMR and by far its most significant predictor. The ratio of the R^2 value resulting from using AGE as the single independent variable to that resulting from using all the variables included in the stepwise regression ranged from 75 to 100 percent. This conclusion is in accord with the findings of other researchers (*4*).

DEPTH

DEPTH, or the thickness of the overlay, was included in four of the eight cases in which it was applicable. The variable was excluded in some cases because the available data set for the group had a distribution with a limited range for the values of this variable. For example, in the Suffolk District, the overlay thickness ranged only from 2.5 to 4.1 cm (1.0 to 1.6 in). Such a small variation had an insignificant impact on the DMR value.

YESAL

The YESAL variable, which represents the average annual ESALs, was included in only two cases, although it was available for all

TABLE 1 Predictor Variables Status for Each Group

Group No.	Description	AGE	DEPTH	YESAL	STRNO	LANNO	RDTYP	ROUTID	DISTR
1	overlaid flex- Bristol	included	included	included	*	not includ.	not includ.	not includ.	**
2	overlaid flex- Salem	included	included	not includ.	included	included	not includ.	not includ.	**
3	overlaid flex- Richmond	included	not includ.	included	*	included	included	included	**
4	overlaid flex- Suffolk	included	not includ.	not includ.	included	***	not includ.	included	**
5	overlaid flex- Culpeper	included	not includ.	not includ.	*	***	***	not includ.	**
6	overlaid flex- Staunton	included	included	not includ.	*	included	***	included	**
7	flex no overlay- region1	included	**	not includ.	not includ.	included	not includ.	not includ	not includ.
8	flex no overlay- region2	included	**	not includ.	not includ.	included	not includ.	included	not includ.
9	composite- 1 overlay	included	not includ.	not includ.	**	***	not includ.	not includ	included
10	composite- > 1 overlay	included	included	not includ.	**	included	***	***	***

* explanatory variable was not available

** explanatory variable is not applicable

*** all points belonged to the same level for the categorical variable, or only 6 points or less were available for the other level.

10 data sets. This finding is quite encouraging, since it means that the adopted classification scheme and the use of dummy variables helped to keep the YESAL virtually at a uniform level within each category, and hence reduced the significance of its role in the overall prediction process. This allows reasonable predictions to be made even in the absence of ESAL data.

STRNO

No true assessment of the significance of the structural number (STRNO) could be made since it was only available and applicable in four data sets. STRNO entered the models in two cases.

LANNO

The dummy variable LANNO, accounting for the lane rated, entered the models in six of seven cases. In the absence of ESAL data this variable becomes essential to account for the difference in the deterioration trends between the traffic and the inner lanes.

RDTYP

RDTYP, which accounts for the number of lanes per direction of the roadway section, was included in one of nine cases. Since YESAL played a minor role in the prediction process, the number of lanes per direction, which influences the share of each lane in the traffic load, should also have an insignificant effect.

ROUTID

The ROUTID set of dummy variables, which identifies the individual routes within a certain group, was included in four of nine cases. ROUTID helped to account for some route-specific characteristics and reduced the significance of the role played by the YESAL and STRNO variables.

DISTR

DISTR, the set of dummy variables used to identify individual districts, was included in one of three cases in which classification was based on geographic region. In addition, statistical tests performed to check whether the deterioration trends for the overlaid flexible pavement category differed among the various districts indicated that DISTR was indeed a significant predictor. For example, when stepwise regression analysis was performed on an experimental data set constructed by pooling points from three districts constituting a geographic region, the DISTR dummy variables were included in the model. This further justifies the subdivision of this category into groups of individual districts.

COMMENTS

Although the main purpose of the linear stepwise regression analysis was merely to identify the significant predictors, the results obtained were quite encouraging. Table 2 summarizes the models' statistics. In general, the models were highly significant, with satis-

TABLE 2 Linear Models Statistics

Group or Data set	R^2 value	Standard Error (SE)	F-value	p-value	No. of observations
1.overlaid flex- Bristol	0.69	3.77	292.51	0.0000	404
2.overlaid flex- Salem	0.66	4.02	253.65	0.0000	534
3.overlaid flex-Richmond	0.44	4,41	115.06	0.0000	861
4.overlaid flex- Suffolk	0.72	3.13	55.09	0.0000	63
5.overlaid flex-Culpeper	0.68	3.40	142.38	0.0000	69
6.overlaid flex- Staunton	0.54	3.82	121.63	0.0000	414
7.flex no overlay-region1	0.50	4.73	48.94	0.0000	96
8.flex no overlay-region2	0.66	3.78	100.51	0.0000	153
9.composite- 1 overlay	0.76	2.38	138.88	0.0000	88
10.composite->1 overlay	0.85	2.36	146.25	0.0000	80

factory coefficients of determination (R^2) coupled with reasonable standard errors.

This stage of the study also indicated the need for minor modifications in the classification scheme. To overcome a problem regarding an incorrect sign for YESAL in the Bristol overlaid flexible model, the group was subdivided into two finer subgroups: Subgroup 1a for I-77 sections and Subgroup 1b for I-81 and I-381 sections. This helped to attain more homogeneous characteristics within the new subgroups, and YESAL disappeared from the equation. In addition, to improve the rather poor fit for the Richmond model, the group was classified into four subgroups: Subgroup 3a for I-64, Subgroup 3b for I-85, Subgroup 3c for I-95 sections with two lanes per direction, and Subgroup 3d for I-95 sections with three or more lanes per direction.

With the classification scheme refined and significant predictors with meaningful signs identified, the study could approach more refined and realistic model forms. However, it is essential to remember that the developed models are empirical and should not be applied beyond the range of the data used in their development. This is especially true since some important variables were missing and others were excluded from the models because their limited range had an insignificant effect on the DMR prediction.

MODEL DEVELOPMENT

Development of Power Prediction Model

The power curve represents a model form that is more realistic than the simple linear model, which fails to meet most of the boundary conditions established for a deterioration model. The power curve model is generally expressed as

$$\begin{aligned}\text{DMR} = \text{DMR}_{\text{init}} - a_0 \cdot (\text{AGE})^{a_1} \cdot (\text{DEPTH})^{a_2} \cdot (\text{STRNO})^{a_3} \\ \cdot (\text{YESAL})^{a_4} \cdot (\text{LANNO})^{a_5} \cdot (\text{RDTYP})^{a_6} \\ \cdot (\text{ROUTID})^{a_7} \cdot (\text{DISTR})^{a_8}\end{aligned} \qquad (2)$$

The power curve model is capable of satisfying the initial boundary condition of no distress at age zero, regardless of the values for the other variables.

Approaches for Fitting Power Curve

There are two options for fitting the power curve to the observed data. The first option is to transform the model into a linear form by taking the logarithm of both sides of the equation. The second approach is to directly fit the model by nonlinear regression techniques. Each of these approaches has its own assumptions and advantages, as well as disadvantages.

The basic assumption of the first approach is that the error term is multiplicative, as follows:

$$\begin{aligned}\text{DMR} = \text{DMR}_{\text{init.}} - a_0 \cdot (\text{AGE})^{a_1} \cdot (\text{DEPTH})^{a_2} \cdot (\text{STRNO})^{a_3} \\ \cdot (\text{YESAL})^{a_4} \cdot (\text{LANNO})^{a_5} \cdot (\text{RDTYP})^{a_6} \\ \cdot (\text{ROUTID})^{a_7} \cdot (\text{DISTR})^{a_8} \cdot \text{error}\end{aligned} \qquad (3)$$

This allows the logarithmic transformation to be performed by taking the natural logarithm of both sides of the equation to yield

$$\begin{aligned}\ln(\text{DMR}_{\text{init.}} - \text{DMR}) = \ln(a_0) + a_1 \cdot \ln(\text{AGE}) + a_2 \cdot \ln(\text{DEPTH}) \\ + a_3 \cdot \ln(\text{STRNO}) + a_4 \cdot \ln(\text{YESAL}) \\ + a_5 \cdot \ln(\text{LANNO}) + a_6 \cdot \ln(\text{RDTYP}) \\ + a_7 \cdot \ln(\text{ROUTID}) + a_8 \cdot \ln(\text{DISTR}) \\ + \ln(\text{error})\end{aligned} \qquad (4)$$

In the present case, however, interest was in the response variable in its original metric (the DMR before transformation). Consequently, a reverse transformation would have to be performed to convert the transformed predicted value back to its original metric. Such a procedure, although it has become common practice, has two complications: (a) the parameter estimates after transformation are no longer the least-squares estimates of the true parameters (*5,6*), and (b) the goodness-of-fit statistics reported in this case strictly apply to the transformed model, and the detransformed regression equation will not usually have the same level of accuracy reported for the transformed one (*7*).

In the second approach the error term is assumed to be additive, and thus the model cannot be transformed. This approach will avoid the problems associated with variable transformation; however, nonlinear regression is much more complex and inconvenient to the user than the simpler linear regression (*8*).

In the current study, after examining the residuals resulting from the two approaches, the assumption of an additive error term seemed more plausible. Consequently, only the results from the nonlinear regression approach are reported.

Use of Nonlinear Regression in Fitting Power Curve

Equation 2 gives the general form for the power model. The predictor variables used for each group or data set were those identified from the stepwise regression. However, since the variables' significance may slightly change with the model form assumed, care was taken not to exclude significant variables that would appreciably improve the fit in this case but were not included in the previous stepwise regression step (this was only the case with Subgroup 3c in connection with the DEPTH variable).

To obtain the initial parameter estimates required by the nonlinear regression search algorithm, the model was transformed into a linear form as described earlier and the parameters were estimated by linear regression. These estimates were then used by the iterative algorithm to find the estimates that would minimize the sum of the square of the residuals. The asymptotic standard errors for the parameters were consistently monitored to ensure that they were within reasonable limits. Table 3 shows the developed models and their accompanying statistics.

Evaluation of Power Curves

To measure the goodness of fit of the developed models, plots were made of the predicted versus the actual DMR values for each of the 14 models developed. A sample of these plots for four groups is provided in Figure 2. No erratic patterns are apparent, and the power model appears to adequately fit the data.

A sensitivity analysis was then conducted on each of the developed models to ensure that their predictions conform with basic engineering knowledge and to assess the relative importance of the different predictors. This mainly involved the generation of three-dimensional and two-dimensional plots showing the change in the

TABLE 3 Power Models and Their Statistics

Group	Model	R^2	SE
1a	$DMR = 100 - 5.17.(AGE)^{0.68}$	0.80	3.24
1b	$DMR = 100 - 4.43.(AGE)^{0.73}.(DEPTH)^{-0.04}$	0.68	3.73
2	$DMR = 100 - 15.63.(AGE)^{0.75}.(DEPTH)^{-0.17}.(STRNO)^{-0.92}.(LANNO)^{-0.31}$	0.67	3.94
3a	$DMR = 100 - 7.08.(AGE)^{0.62}.(YESAL)^{0.28}$	0.72	3.42
3b	$DMR = 100 - 7.07.(AGE)^{0.44}.(YESAL)^{0.3}$	0.65	3.27
3c	$DMR = 100 - 5.06.(AGE)^{0.48}.(YESAL)^{1.29}.(DEPTH)^{-0.20}$	0.72	3.03
3d	$DMR = 100 - 2.30.(AGE)^{0.42}.(YESAL)^{1.53}.(LANNO)^{-0.16}$	0.50	4.15
4	$DMR = 100 - 1.67.(AGE)^{0.92}.(ROUT64)^{0.31}$	0.71	3.24
5	$DMR = 100 - 1.14.(AGE)^{1.18}$	0.68	3.40
6	$DMR = 100 - 3.14.(AGE)^{0.62}.(DEPTH)^{-0.15}.(LANNO)^{-0.59}.(ROUT81)^{0.08}$	0.57	3.69
7	$DMR = 100 - 6.03.(AGE)^{0.49}.(LANNO)^{-0.11}$	0.59	4.37
8	$DMR = 100 - 1.82.(AGE)^{0.79}.(LANNO)^{-0.21}.(ROUT95)^{0.21}$	0.68	3.74
9	$DMR = 100 - 3.45.(AGE)^{0.76}.(DISTR5)^{-0.35}$	0.74	2.50
10	$DMR = 100 - 3.43.(AGE)^{0.76}.(DEPTH)^{-0.23}.(LANNO)^{-0.68}$	0.87	2.21

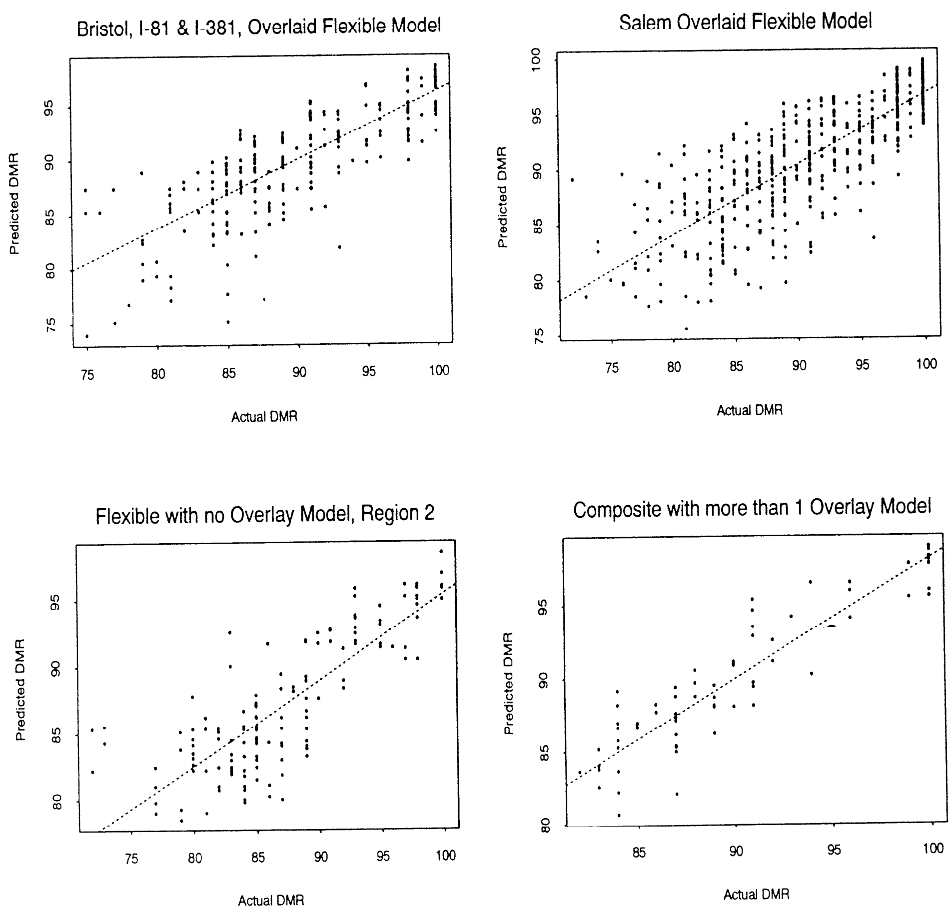

FIGURE 2 Goodness of fit for power model.

DMR value with the variable(s) of interest. A sample of these plots is given in Figure 3 for the Salem model. Results for the other models are reported elsewhere (9). These plots showed the predicted deterioration trends to be quite reasonable.

Development of Sigmoidal Prediction Model

A sigmoidal (S-shaped) model is a curve with an inflection point and upper and lower asymptotes. The sigmoidal model could be an appropriate form for predicting pavement condition indexes, since such indexes are typically bounded by an upper and a lower value. Moreover, by having an inflection point, the model is capable of reflecting different deterioration rates throughout the pavement service life.

Since the sigmoidal model form offers such desirable characteristics, it was applied to Virginia's data. The performance of the developed sigmoidal models was then compared with the simpler power models developed in the previous step to assess whether the sigmoidal model significantly enhanced prediction accuracy.

Model Form and Initial Parameter Estimates

The sigmoidal model that was assumed had the following general form:

$$\mathrm{DMR} = 100 - a_0 \cdot \exp \times \left[\frac{- a_1 \cdot (\mathrm{DEPTH})^{a_2} \cdot (\mathrm{STRNO})^{a_3} \cdot (\mathrm{LANNO})^{a_4} \cdot (\mathrm{RDTYP})^{a_5} \cdot (\mathrm{ROUTID})^{a_6} \cdot (\mathrm{DISTR})^{a_7}}{(\mathrm{AGE})^{a_8} \cdot (\mathrm{YESAL})^{a_9}} \right] \quad (5)$$

The variables included for each category or data set were those identified from stepwise regression. To obtain the initial parameter estimates, the model was rearranged and transformed into a linear form by taking the logarithm of both sides of the equation twice to yield the following form:

$$\begin{aligned} \ln\left[-\ln\left(\frac{100 - \mathrm{DMR}}{a_0}\right)\right] = {} & \ln \cdot a_1 + a_2 \cdot \ln(\mathrm{DEPTH}) \\ & + a_3 \cdot \ln(\mathrm{STRNO}) \\ & + a_4 \cdot \ln(\mathrm{LANNO}) + a_5 \cdot \ln(\mathrm{RDTYP}) \\ & + a_6 \cdot \ln(\mathrm{ROUTID}) + a_7 \cdot \ln(\mathrm{DISTR}) \\ & - a_8 \cdot \ln(\mathrm{YESAL}) - a_9 \cdot \ln(\mathrm{AGE}) \end{aligned} \quad (6)$$

According to the model specification, the parameter a_0 represents the difference between the values of the upper and the lower asymptotes of the curve. Since the lower range for the available DMR data was generally at about a DMR score of 70, the parameter a_0 was initially assumed to be equal to 30. This allowed for calculating the left-hand side of Equation 6, and linear regression was then used to estimate the remaining parameters.

Nonlinear Regression

Using the initial parameter estimates from the previous step, nonlinear regression was performed on the original model specification (Equation 5) to develop the desired models. Table 4 shows the developed models and their statistics. A satisfactory model could be obtained for only eight groups; for the other six groups the asymptotic error values were too high to be acceptable.

Evaluation of Sigmoidal Model

The goodness of fit for the sigmoidal models was evaluated in much the same way as it was for the power models. Figure 4 shows the evaluation results for four groups, in which it can be seen that on

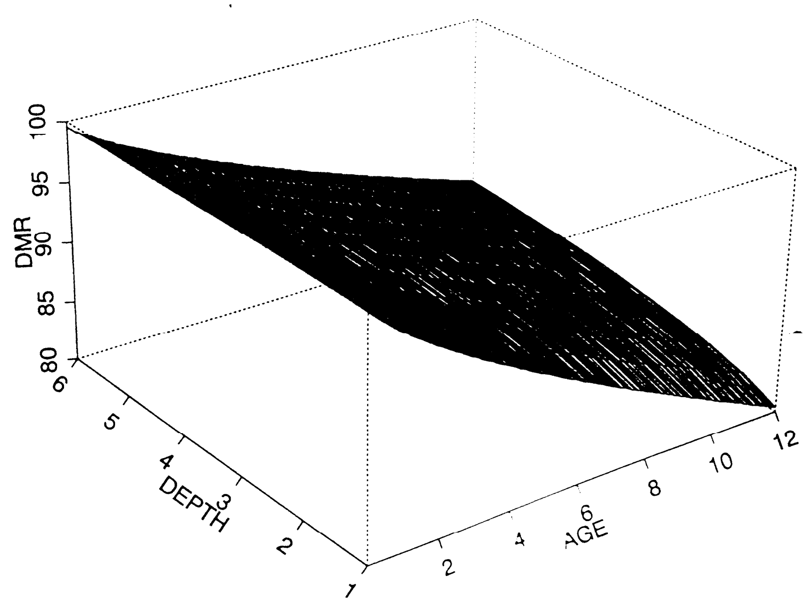

FIGURE 3 Three-dimensional sensitivity analysis for Salem model, where STRNO = 6.0 and LANNO = 0.

TABLE 4 Sigmoidal Models and Their Statistics

Group No.	Model	R^2	SE
1a	$DMR = 100 - 43.96\, e^{\frac{-2.49}{(AGE^{0.56}}}$	0.83	3.02
1b	$DMR = 100 - 23.52\, e^{\frac{-2.14\,.\,(DEPTH)^{0.21}}{(AGE)^{1.02}}}$	0.73	3.44
2	$DMR = 100 - 28.68\, e^{\frac{-0.74\,.\,(DEPTH)^{0.25}.\,(STRNO)^{0.80}.\,(LANNO)^{0.34}}{(AGE)^{0.76}}}$	0.70	3.78
3d	$DMR = 100 - 30.88\, e^{\frac{-6.05\,.\,(LANNO)^{0.24}}{(YESAL)^{1.81}.\,(AGE)^{0.50}}}$	0.52	4.08
6	$DMR = 100 - 18.46\, e^{\frac{-1.88\,.\,(DEPTH)^{0.66}.\,(LANNO)^{0.92}}{(AGE)^{0.83}}}$	0.62	3.51
7	$DMR = 100 - 21.22\, e^{\frac{-6.50\,.\,(LANNO)^{0.47}}{(AGE)^{1.85}}}$	0.70	3.77
8	$DMR = 100 - 25.67\, e^{\frac{-9.56\,.\,(LANNO)^{0.37}}{(ROUT95)^{0.16}.\,(AGE)^{1.18}}}$	0.71	3.55
10	$DMR = 100 - 25.74\, e^{\frac{-2.48\,.\,(DEPTH)^{0.36}.\,(LANNO)^{0.70}}{(AGE)^{0.80}}}$	0.90	1.95

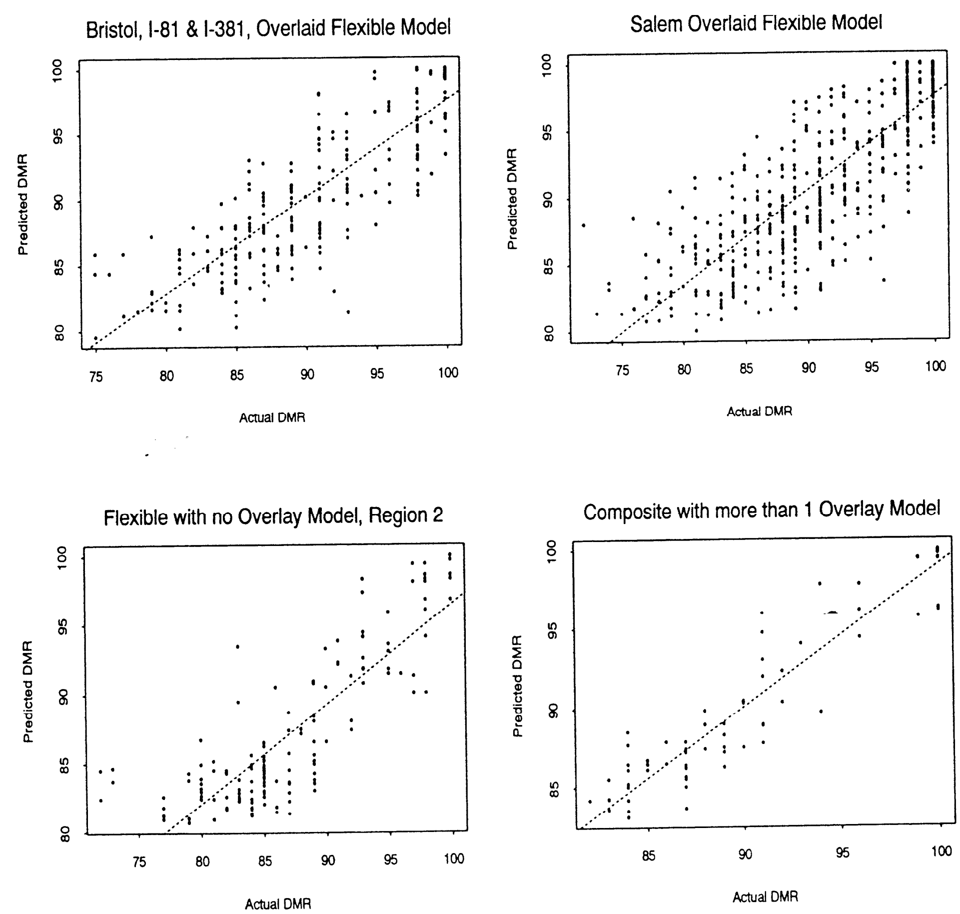

FIGURE 4 Goodness of fit for sigmoidal model.

convergence the sigmoidal model also provided an adequate fit. To ensure the reasonableness of the models' predictions, sensitivity analyses were performed (9).

Sigmoidal Model Versus Power Curve

Figure 5 contrasts the deterioration trends given by the power and sigmoidal models for the eight categories for which a satisfactory sigmoidal model could be developed. These plots were made assuming typical values for the section characteristics in each data set. The plots show that, unlike the power curve, the sigmoidal model can model a low-deterioration-rate region at the beginning of the section's life cycle. This helps explain the sigmoidal model's nonconvergence for some groups. In such cases sections essentially exhibited the same deterioration rate throughout their lives.

The plots also indicate that the differences between the sigmoidal model low-deterioration-rate region and the power curve are of appreciable significance only in the flexible pavements with no overlay category. This is a reasonable conclusion, since distress should be expected to develop in original flexible pavement designs at a slower rate than in overlays or composite pavements.

An investigation of the R^2 and the standard error (SE) values for the two model forms given by Tables 3 and 4 supports this conclusion. The sigmoidal model provided an improved fit for the groups in which it converged, with the greatest improvement obtained for the flexible pavements with no overlay category in Region 1.

• In summary, the following conclusions can be drawn from the available data: For all pavement types other than the flexible pavements with no overlay category, the sigmoidal model may provide a slightly better fit, but the use of the simpler power curve is ade-

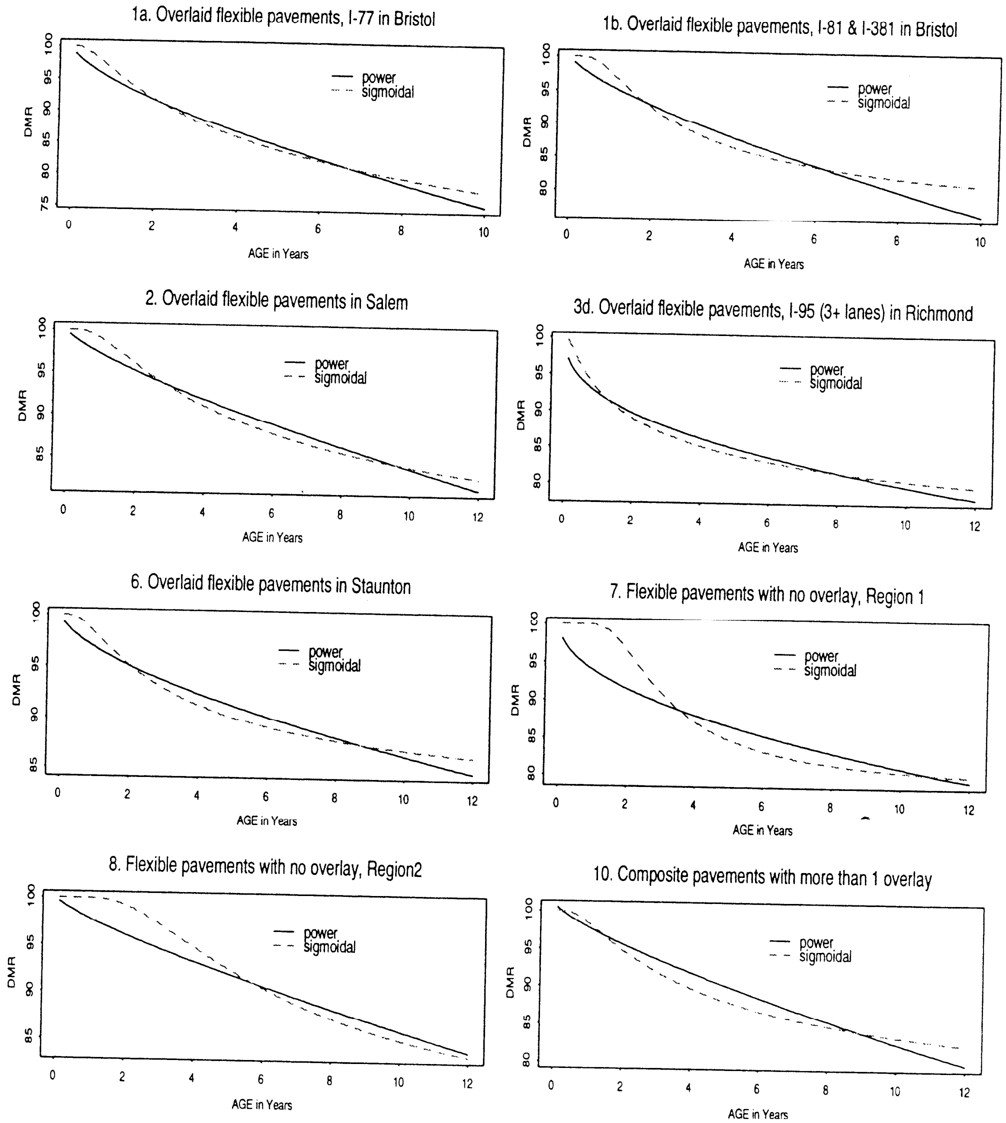

FIGURE 5 Comparing sigmoidal and power models.

quate from a practical standpoint. This conclusion is supported by the fact that the sigmoidal model failed to converge for some groups belonging to these pavement types.

- For flexible pavements with no overlay, the sigmoidal curve may be preferred over the power curve to reflect their slower initial deterioration rate. The significant improvement in the fit for Group 7 justifies this conclusion.

ASSESSING MODELS' ACCURACIES

Approaches for Adjusting Developed Models

Since the behaviors of pavement structures are affected by many factors, the performance of a specific pavement section typically differs from the mean response given by a deterioration model. In practice, therefore, when the observed condition of a section in a given year differs from that predicted by the model, the model is adjusted to pass through the observed point. Predictions for future years are then made with this augmented curve.

The literature on prediction model development shows two basic approaches for model adjustment. The first, exemplified by the PAVER system and the Illinois Pavement Feedback System, essentially draws a curve through the observed pavement condition–age point parallel to the developed model. Mathematically, this is done by solving the model equation for the AGE value that corresponds to the observed condition. Future predictions are then made assuming that this calculated value is the section's current age (*10,11*).

The second approach diverts the curve vertically so that it passes through the observed point. This is done by using the actual drop in the pavement condition index from its initial value (D_1) versus the theoretical drop (D_2) to compute an adjustment factor (F), defined as $F = D_1/D_2$. Future predictions are made by multiplying the theoretical drop by F, which is usually constrained to the interval of 0.75 to 1.25 (*12*).

Both adjustment methods were examined in the current study to determine if either of them was more appropriate than the other.

Measuring Accuracy of Prediction Process

As reported elsewhere (*2*) a 5 percent sample of datum points was randomly selected following the data base construction stage. This sample was not used during model development so that it could serve as a verifying set for the models once they were developed. The size of this sample, however, allowed an assessment of only the overlaid flexible models of the Bristol, Salem, Richmond, and Staunton districts. Since the sample datum points belonged to different survey years and to sections with different ages, the points were categorized into groups to allow for the measurement of the accuracy of prediction for different years into the future.

Accuracy Assessment Results

The models' adjusted predictions were compared against the observed DMR values from this sample data set. Figure 6 shows a typical example of these comparisons for the Salem District. In this example predictions were made by using the power model and were adjusted by the horizontal shift adjustment approach.

For a quantitative assessment of the models' accuracy, the prediction error, defined as the difference between the observed and the predicted value, was calculated for each observation point. The mean of this prediction error, its standard deviation, and 95 percent confidence intervals were then computed for each district and each prediction level (number of prediction years into the future). The results of these calculations for the case given in Figure 5 are as follows:

Number of Prediction Years	*Mean*	*Standard Deviation*	*95% Confidence Interval*
1	−0.38	3.37	−2.11; 1.35
2	−0.97	3.23	−2.52; 0.60
3 or 4	−1.76	3.54	−3.80; 0.28
5+	−0.80	4.53	−3.20; 1.60

These data indicate that the accuracy was quite satisfactory even for predictions for 5 or more years into the future. The results for the other three districts were quite similar (*9*).

Comparing Performances of Two Model Forms and Two Adjustment Methods

To compare the model forms and adjustment approaches, the predicted DMR values were computed according to the power and the sigmoidal models, with each one being adjusted by using the horizontal and vertical shift approaches. The linear model was not considered in this comparison since it failed to meet the boundary conditions established for a deterioration model. For each datum point, four predicted values were estimated, corresponding to the two model forms times the two adjustment procedures, except for the Richmond District, for which the sigmoidal curve did not converge.

An analysis-of-variance test was then performed to assess the effects on the response variable, or the prediction error, of the following three factors:

1. The number of years into the future for which prediction is performed,
2. The model form, and
3. The adjustment method used.

For all four districts the interaction between these three factors was found to be insignificant. This allowed for the study of the effects of the individual factors, which were also found to be insignificant, leading to the following conclusions:

1. For overlaid flexible pavements, no significant differences between the predictive accuracies of the two model forms existed.
2. The accuracies of the predictions for different years were comparable.
3. The performances of the two adjustment procedures were similar.

CONCLUSIONS

In the present study models for predicting the deterioration of Virginia's Interstate pavements were developed. The models were evaluated and shown to provide for an adequate fit and predictions that agreed with logic. Comparing the models' predictions with observed values from a sample data set not used in their development demonstrated their accuracy to be quite reasonable even for long-range prediction.

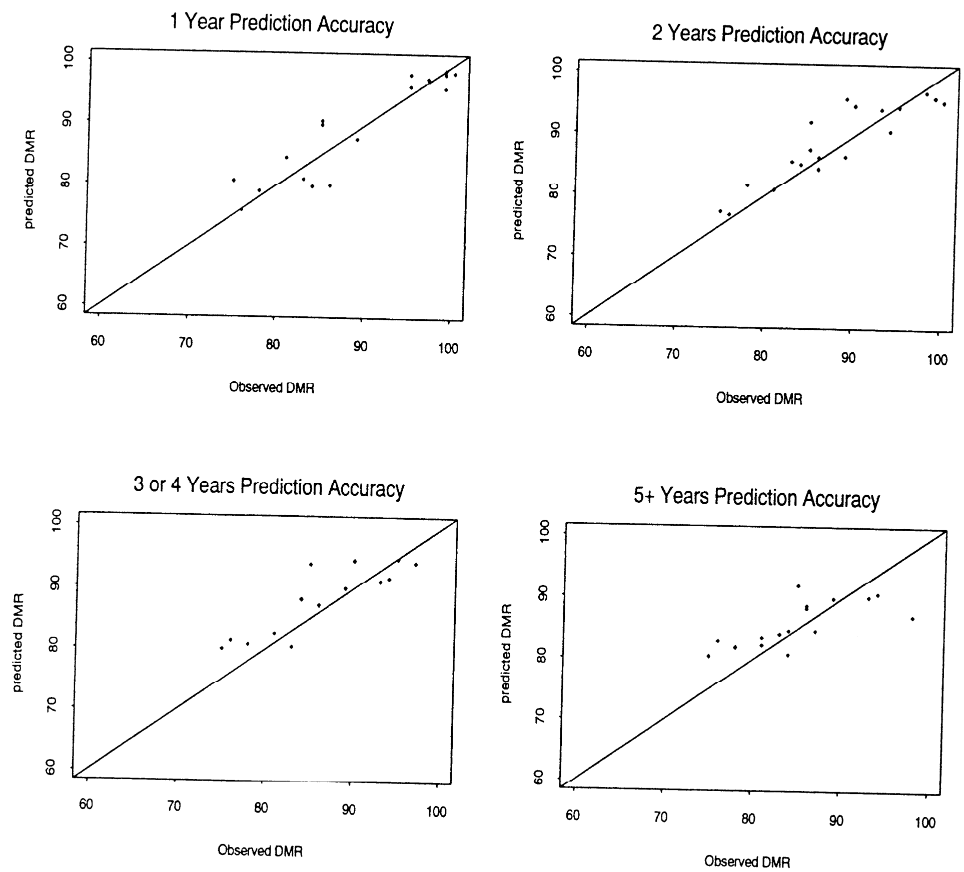

FIGURE 6 Assessing prediction accuracy for Salem District.

Although the study focused on Virginia's data, many of the following conclusions may be applicable elsewhere:

1. By adopting an appropriate classification scheme, pavement age can be the most significant predictor of deterioration. This allows prediction to be based on information that is readily available in almost every pavement management system.
2. The use of dummy variables to differentiate between different routes or districts helps to account for some of the route- or district-specific characteristics.
3. Although the linear model form fails to meet most of the boundary conditions, it can be used to identify the significant variables affecting deterioration. It may also be useful for identifying desirable modifications in the modeling approach before experimenting with more elaborate model forms.
4. For all pavement types other than the flexible pavements with no overlay category, a power model form seems adequate from a practical standpoint. For nonoverlaid flexible pavements, the sigmoidal model may be preferred.
5. There is no evidence to suggest that either the horizontal or the vertical shift adjustment approach is more appropriate than the other.

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