Development of Pavement Performance Models by Combining Experimental and Field Data

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Abstract: The objective of this paper is to demonstrate the development of pavement performance models by combining experimental and field data. A two step approach was used. In the first step a riding quality model based on serviceability consideration is developed. The data set of the American Association of State Highways Officials (AASHO) Road Test is used to this effect. Due to the experimental nature of the AASHO Road Test data set, some of the estimated parameters of the model may be biased when the model is to be applied to predict performance in the field. In the second step, the original model parameters are reestimated by applying joint estimation with the incorporation of field data set. This data set was collected through the Minnesota Road Research Project (MnRoad). The final model is referred to as the joint model, and it can be used to predict the performance of in-service pavement sections. Joint estimation allowed for the full potential of both data sources to be exploited. First, the effect of variables not available in the first data source were identified and quantified. Further, the parameter estimates had lower variance because multiple data sources were pooled, and biases in the parameters of the experimental model were corrected. Finally, different measurements of the same property were incorporated by using a measurement error model. Thus, the methodology proposed in this paper makes optimum use of available data and yields models of improved statistical properties compared with techniques such as ordinary least squares.

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Introduction

The accurate prediction of pavement performance is important for efficient management of the transportation infrastructure. By reducing the prediction error of pavement deterioration, agencies can obtain significant budget savings through timely intervention and accurate planning (Madanat 1993).

At the network level, pavement performance prediction is essential for adequate activity planning, project prioritization and budget and resource allocation. At the project level, it is important for establishing the specific corrective actions needed, such as maintenance and rehabilitation.

Pavement deterioration models are not only important for highway agencies to manage their road network, but also in road pricing and regulation studies. Both the deterioration of the pavement over time and the relative contribution of the various factors to deterioration are important inputs into such studies. Useful models should be able to quantify the contribution to pavement deterioration of the most relevant variables. Some of these variables are the pavement structure (materials and strength), traffic (axle configuration and axle loads) and environment conditions (temperature and moisture).

The objective of this paper is to demonstrate the development of pavement performance models by combining experimental and field data. The approach followed in this paper combines data of in-service pavements with data from experimental studies, by using joint estimation, a statistical method that was designed specifically for the purpose of parameter estimation with multiple data sets. Joint estimation is particularly well suited to problems in which different data sources have different levels of precision, or where they are suspect of suffering from one or more type of bias, which is the case in highway pavement deterioration modeling. In this context, data obtained from field studies are likely to be less precise than those obtained from accelerated tests, due to correlation among explanatory variables, etc. On the other hand, experimental data are likely to suffer from biases, as they do not represent the true deterioration mechanisms of pavements.

The method of joint estimation has been applied successfully to a variety of problems in transportation planning and engineering including the estimation of travel demand models (Ben-Akiva and Morikawa 1990). More recently, Archilla and Madanat (2001) have used the method of joint estimation to develop pavement deterioration models by combining data from two experimental data sets. The present paper focuses on investigating the feasibility and desirability of applying joint estimation with experimental and field data, to the prediction of pavement roughness progression.

Data Sources for Performance Model Development

Different data sources have been used to develop pavement deterioration models. The major sources are: (1) randomly selected

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in-service pavement sections, (2) purposely built pavement test sections subjected to the action of actual highway traffic and the environment, and (3) purposely built pavement test sections subjected to the accelerated action of traffic and environmental conditions. The first two types of data are known as field data, whereas the last one is referred to as experimental data.

Data from actual in-service pavement sections subjected to the combined actions of highway traffic and environmental conditions are the most representative of the actual deterioration process. All other data sources produce models that are likely to suffer from some kind of bias unless special considerations are taken into account during the estimation of the parameters of the model. However, data from in-service pavements also suffer from several limitations. The most common problems encountered in models developed from randomly selected in-service pavement sections are caused by the presence of multicollinearity between relevant explanatory variables, unobserved events typical of such data sets, and the problem of endogeneity bias caused by the use of endogenous variables as explanatory variables (Greene 2000). These are discussed separately below.

The problem of multicollinearity is typical of time-series pavement performance data sets. Variables such as pavement age and accumulated traffic are usually almost perfectly collinear. Hence, the estimated models usually fail to identify the effects of both variables simultaneously. While multicollinearity does not introduce biases in the model parameter estimates, it lowers confidence in their significance. Experimental data do not usually suffer from this problem, because the application of traffic loading to the pavement sections can be accelerated, thus reducing the correlation with pavement age.

Data gathering surveys during experimental tests are usually of limited duration. Thus, if only the events observed during the survey are considered in the statistical analysis (ignoring the information of the after and before events), the resulting models would suffer from truncation bias. If the censoring of the events is not properly accounted for, the model may suffer from censoring bias (Prozzi and Madanat 2000).

Another common problem is endogeneity bias, which arises when models to predict pavement life are developed. Pavements that are expected to carry higher levels of traffic during their design life are designed to higher standards. The bearing capacity of these pavements is higher than those designed to withstand lower traffic levels. Thus, any explanatory variable that is an indicator of a higher bearing capacity, such as the structural number, will be an endogenous variable that is determined within the model and cannot be assumed to be exogenous. If such a variable were incorporated into the model, the estimated parameters would suffer from endogeneity bias (Madanat et al. 1995). Another case of endogeneity bias occurs when maintenance (which is triggered by the condition of the pavement) is used as an explanatory variable (Ramaswamy and Ben-Akiva 1990).

The latter two problems can be addressed using statistical techniques that take into account the presence of truncation or endogeneity or, alternatively, by developing models that are based on experimental data. However, experimental data have their own biases, because they do not represent the true deterioration processes of in-service pavements. Joint estimation with both field and experimental data can be used to correct for these biases. Archilla and Madanat (2001) have successfully developed models to predict pavement rutting by combining two data sources. Both data sources used in their research were experimental tests. Thus, their models are conditional on the experimental traffic. The next logical step in this line of research is to investigate the transferability of these models to actual mixed highway traffic.

Proposed Methodology

Based on the above considerations a two step approach was used in this research. In the first step a riding quality model based on serviceability consideration is developed. The data of the American Association of State Highways Officials (AASHO) Road Test are used to this effect. By using data originated from a well-conceived experiment many of the potential problems highlighted in the previous section are avoided. Due to the experimental nature of the AASHO Road Test data set, some of the estimated parameters of the model may be biased when the model is to be applied to predict performance in the field. In the second step, the parameters of the original model (or serviceability model) are reestimated by applying joint estimation with the incorporation of field data set. This data set corresponds to the Minnesota Road Research Project. The final model is referred to as the joint model, and it can be used to predict the performance of in service pavement section.

The AASHO Road Test

The AASHO Road Test was sponsored by the American Association of State Highways Officials (AASHO) and was conducted from 1958 through 1960 near Ottawa, Ill. (HRB 1962). The data from this experiment constitutes the most comprehensive and reliable data set available to date. The site was chosen because the soil in the area is representative of soils corresponding to large areas of the Midwestern United States and it was fairly uniform. The climate was also considered to be representative of many states in the northern part of the country. The average temperature during the summer months was 76°F (25°C) while the average temperature for the winter months was 27°F (−3°C). The soil remained mostly frozen during the winter months with the depth of frost penetration depending on the length and severity of the cold season. Only one subgrade material and one climatic region were evaluated during the AASHO experiment.

The test tracks consisted of two small loops (numbered 1 and 2) and four large loops (numbered 3 through 6). Each loop constituted a segment of a four-lane divided highway, whose north tangents were surfaced with asphalt concrete (AC) and the south tangents with Portland cement concrete (PCC). Therefore, each loop consisted of four traffic lanes, two with AC surfaces and two with PCC surfaces. Only the flexible pavement sections were analyzed in our research. Loops 2 through 6 were subjected to experimental truck traffic whose load was strictly controlled. All the vehicles assigned to any one traffic lane had the same axle arrangement and axle load configuration.

A total of 142 flexible pavement sections were built into the various loops. Each section covered the two lanes, and each lane was subjected to a different traffic configuration, so the total number of test sections was 284. Out of this total, there were 252 original test sections and 32 duplicate sections. Only the data corresponding to the original 252 test sections were used for the estimation of the parameters of the model. The remaining data from the 32 replicated sections were kept apart to test the validity of the estimated models. The riding quality of the various sections was monitored in terms of their serviceability by means of the Present Serviceability Index (PSI).

Most of the sections on the flexible pavement tangents were part of a complete experimental design. The design factors considered were surface thickness, base thickness, and subbase thickness. In each of the loops, three levels of surface thickness were combined with three different base thicknesses and three levels of subbase thicknesses. The surface thickness of the pavement sections, comprising the main experimental design (loops 2 through 6), varied from 1 to 6 in. (25–150 mm), in intervals of 1 in. (25 mm). The base layer varied in thickness from 0 (no base layer) to 9 in. (0–225 mm), in increments of 3 in. (75 mm). The thickness of the subbase layer varied from 0 (no subbase layer) to 16 in. (0–400 mm), in increments of 4 in. (100 mm).

The materials used for the construction of the AC surface, base, and subbase layers were the same for all sections. Hence, the effect of the material properties on pavement performance cannot be directly assessed from the data of the main experimental design. Other experiments aimed at assessing different surface and base materials were also conducted during the AASHO Road Test, but were not part of the main experimental design. Therefore, these data were not considered in the development of the models presented in this research.

Original AASHO Model

The first pavement performance model developed was based on the data provided by the AASHO Road Test. The AASHO equation estimates pavement deterioration based on the definition of a dimensionless parameter g referred to as *damage*. The damage parameter was defined as the loss in the value of the Present Serviceability Index (PSI) at any given time

$$g_t = \frac{p_0 - p_t}{p_0 - p_f} = \left(\frac{N_t}{\rho}\right)^{\omega} \tag{1}$$

where g_t = dimensionless damage parameter; p_t = serviceability at time t (in PSI units); p_0 = initial serviceability at time $t=0$; p_f = terminal serviceability; N_t = cumulative number of equivalent 80 kN single axle loads applied until time t; and ρ, ω = regression parameters.

This deterioration model was estimated based on data obtained from AASHO Road Test. The data from the AASHO Road Test provided little information on long-term environmental effects and no direct information on the pavement response and performance under actual highway traffic.

The parameters ρ and ω were obtained for each pavement test section by applying Eq. (1) in a stepwise linear regression approach. Some of the details of the estimation approach followed are not very clear in the literature. Once the values of ρ and ω were estimated, the estimated values were expressed as a function of design and load variables, and two new linear regressions were carried out. The assumed relationship between ω and these variables was (HRB 1962)

$$\omega = \omega_0 + \frac{b_0 (L_1 + L_2)^{b_2}}{(a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4)^{b_1} L_2^{b_3}} \tag{2}$$

where L_1 = axle load (in kips); $L_2 = 1$ for single axle vehicles, 2 for tandem axle vehicles; ω_0 = a minimum value assigned to ω; b_0–b_3 = regression parameters; a_1–a_4 = regression parameters that were obtained by performing analyses of variance; and D_1–D_3 = thicknesses of the surface, base, and subbase layer, respectively.

The specification form for the relationship between ρ (expected pavement life to a selected terminal serviceability value) and the design and load variables was the following:

$$\rho = \frac{\beta_0 D^{\gamma_1} L_2^{\gamma_3}}{(L_1 + L_2)^{\gamma_2}} \tag{3}$$

where $D = a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4$, represents the thickness index; and γ_1–γ_3 = regression parameters.

The statistical approach used to estimate the model parameters has some inconsistencies. The most serious was the improper treatment of censored observations: pavement sections that had not failed by the end of the experiment were ignored in the estimation of the parameters. Moreover, Eqs. (2) and (3) are misspecified because the term $(L_1 + L_2)$ is the sum of a load variable and a dummy variable, thus adding variables with different units. Despite the identified shortcomings of the model specification and the estimation approach, Eq. (1) (or subsequent modification of it) has been used as the basis for pavement design for approximately 50 years [American Association of State Highways and Transportation Officials (AASHTO 1993)].

Specification of the Model with Experimental Data

Basic Model

The data corresponding to the AASHO Road Test was selected for the development and estimation of the experimental pavement deterioration model, referred to as the serviceability model. This experimental data set was chosen because load and structural variables were selected following an experimental design, thus avoiding the problems of multicollinearity and endogeneity discussed in the previous section. As stated earlier, during the AASHO Road Test, the deterioration of the pavement riding quality was determined by the change in the Present Serviceability Index (PSI) or simply, serviceability. The following form was adopted for predicting the loss of serviceability:

$$y = f(z) = a + bz^c \tag{4}$$

where y = dependent variable representing pavement serviceability; z = independent variable representing some measure of cumulative traffic; a = parameter or function that represents the initial serviceability; b = parameter that represents the rate of change of serviceability; and c = parameter or function that represents the curvature of the function.

The initial value of the serviceability, represented by a in Eq. (4), depends on the construction technology and the final thickness of the asphalt surface.

For a given pavement structure, pavement serviceability decreases as traffic increases. This condition is represented by the sign of the parameter b, because any measure of traffic (z) has a positive sign. Hence, the sign of b is expected to be negative. Furthermore, for a given traffic level, pavement serviceability decreases more rapidly for weaker pavements. This is represented by the absolute value of the parameter or function b. The value of b is thus expected to be a decreasing function with pavement strength.

The form of Eq. (4) is suitable for predicting pavement serviceability at any time in the life of the pavement, therefore, suitable for design. From a pavement management perspective (e.g., budget planning, resource allocation), an incremental form is more beneficial since condition data are usually available on a regular basis and predictions are only desired for the next few time periods (typically one or two years). The incremental form also facilitates the effortless incorporation of seasonal effects and maintenance activities, if desired. In addition the incremental specification may reduce potential heteroskedasticity.

By using a first order Taylor series approximation, the same specification given in Eq. (4) can also be used in its incremental form

$$y_t = y_{t-1} + f'(z_{t-1})(z_t - z_{t-1}) \tag{5}$$

Thus, the specification form for the incremental model in terms of serviceability and some measure of cumulative traffic can be specified as

$$p_t = p_{t-1} + dN_{t-1}^{e} \Delta N_t \tag{6}$$

where p_t = serviceability in PSI at time t; N_{t-1} = cumulative equivalent traffic up to time $t-1$; ΔN_t = equivalent traffic increment from time $t-1$ to time t; and d, e = function and parameter to be estimated, respectively.

By applying the recursive Eq. (6) from the beginning of the life of the pavement, the following expression is obtained:

$$p_t = p_0 + \sum_{\ell=1}^{t} dN_{\ell-1}^{e} \Delta N_\ell \tag{7}$$

where p_0 = initial serviceability in PSI at time $t=0$.

Specification for Initial Serviceability

As indicated earlier, the initial value of serviceability of actual in-service flexible pavement sections never does reach the theoretical value of 5.0 PSI for a perfectly planar surface. The initial value [p_0 in Eq. (7)] depends on the construction quality, the conditions of the working platform on top of which the asphalt surface layer is placed and compacted, and the total thickness of the surface layer (AASHTO 1993).

As the thickness of the asphalt surface layer increases, it is usually constructed in various sublayers or lifts. Each lift provides additional support and improved working conditions for the construction equipment, leading to a better riding quality of the finished surface. Thus, the initial serviceability could be represented as an increasing function of the asphalt layer thickness, as was observed during the AASHO Road Test (HRB 1962). This condition is taken into account in the specification by the following exponential function:

$$p_0 = \beta_1 + \beta_2 \exp\{\beta_3 \ H_1\} \tag{8}$$

where $\beta_{1,2,3}$ = parameters to be estimated; and H_1 = total thickness of the asphalt surface layer.

Specification for Structural Strength

The function d in Eq. (7) is a decreasing function of the strength of the pavement. That is, for stronger pavement structures, serviceability decreases slower than for weaker pavements. The specification of the function d is based on the concept of thickness index developed after the AASHO Road Test (HRB 1962). The thickness index is given by

$$D = a_1 D_1 + a_2 D_2 + a_3 D_3 \tag{9}$$

where D = thickness index; D_1, D_2, D_3 = thickness of the surface, base and subbase layers, respectively; and a_1, a_2, a_2 = layer strength coefficients, whose estimated values were 0.44, 0.14, and 0.11, respectively.

In this research, an alternative designation is proposed to differentiate the present specification from the specification developed during the initial analysis of the AASHO Road Test. Although the regression parameters in Eqs. (9) and (10) are intended to capture the same properties, they are not the same. Thus, the function d is assumed to depend on the equivalent thickness (ET) according to the following specification:

$$d = \mathrm{ET}^{d_0} = (1 + \beta_4 \ H_1 + \beta_5 \ H_2 + \beta_6 \ H_3)^{\beta_7} \tag{10}$$

where H_1, H_2, H_3 = thickness of surface, base and subbase layers, respectively; $\beta_{4,5,6,7}$ = parameters to be estimated; and ET = equivalent thickness.

Since the value of the function d decreases as the pavement strength increases, the parameter β_7 is expected to be negative. The parameters β_4, β_5, and β_6 in Eq. (10) represent the contribution of the asphalt surface, base, and subbase to the total pavement strength. They are expressed relative to the contribution of the subgrade to resist pavement deterioration in terms of serviceability loss. This approach is slightly different from the one utilized during the initial analysis of the AASHO Road Test. However, the relative values of the parameters should be comparable to those in the original study (HRB 1962).

Environmental Considerations

Environmental conditions are of paramount importance in pavement deterioration. In the context of the AASHO Road Test, the most relevant environmental factor is the effect of the freeze–thaw cycles. At low temperatures the asphalt concrete becomes very stiff and its behavior is similar to that of a Portland cement concrete slab. The presence of moisture decreases the interparticle friction of the untreated materials, resulting in an important loss of material strength and stiffness. In turn, this results in loss of support of the asphalt concrete surface layer, inducing increased strain levels for the same applied traffic load. As tensile strains in the asphalt concrete increase, so does the rate of deterioration of the pavement structure. For instance, as the applied tensile strain of the asphalt concrete increases, cracking of the layer would initiate earlier and would propagate faster. To account for the effect of moisture on performance, an environmental factor was developed that augments or diminishes the structural resistance of the pavement depending on the prevailing environmental conditions.

Three distinctive deterioration phases were observed in the pavement sections of the AASHO Road Test as characterized by their loss of serviceability:

1. A *normal phase* characteristic of the summer and fall periods during which the serviceability decreases at a fairly uniform rate;
2. A *stable phase* characteristic of the winter period during which the riding quality of the test sections remained very stable—the serviceability did not decrease significantly; and
3. A *critical phase* during which the rate of deterioration increased significantly and rapidly compared to the previous two phases. This phase corresponded to the spring months.

Furthermore, it was observed that the three phases described above corresponded to the periods of zero frost penetration, increasing depth of frost penetration, and decreasing depth of frost penetration, respectively. Hence, the *frost penetration gradient* variable was included to capture the effect of environmental conditions on pavement deterioration in the form of loss of serviceability. The effect of frost penetration on the loss of serviceability is represented graphically in Fig. 1.

The frost penetration gradient in period t, G_t, is defined as the ratio between the change in the depth of frost penetration during period t and the length of period t. This is accounted for in the specification by the introduction of an environmental factor (F_e) that multiplies the value of the function d in Eq. (7). The expression for the environmental factor is as follows:

$$F_e = \exp\{\beta_8 \ G_t\} \tag{11}$$

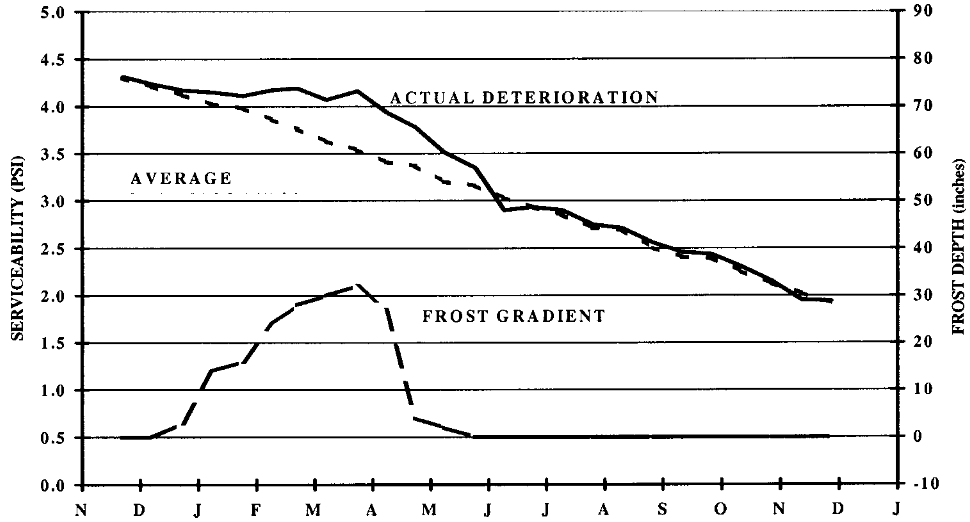

Fig. 1. Averaged observed effect of frost depth on deterioration at AASHO

where G_t = frost penetration gradient; and β_8 = parameter to be estimated.

Based on Eq. (11), three situations are possible:

1. When the depth of frost penetration is constant $(G_t=0)$, F_e is equal to one so the rate of loss in serviceability is unaffected (normal phase);
2. When the depth of frost penetration is increasing $(G_t>0)$, F_e should be smaller than one, thus reducing the rate of serviceability degradation (stable phase); and
3. When the depth of frost penetration is decreasing $(G_t<0$, typical of spring months), F_e ought to be larger than one, thus increasing serviceability degradation (critical phase).

Specification for Aggregate Traffic

A generalization of the traditional approach of aggregating all traffic into its equivalent number of standard 18,000 lb (18 kips) single axle loads is used in this research. This number is usually referred to as the number of equivalent single axle loads (ESALs). All axle load configurations are converted into their equivalent number of ESALs by means of a load equivalence factor (LEF). The most commonly used form for the determination of the LEF is the following:

$$\mathrm{LEF}=\left(\frac{L}{18}\right)^{\eta} \tag{12}$$

where LEF = load equivalence factor; L = axle load in kips (1,000 lb); and η = regression parameter.

The LEF multiplied by the actual number of axles of that given load, L, yields the number of equivalent single axle loads (ESALs). This expression was developed based on the findings of the initial analysis of the AASHO Road Test data. It should be borne in mind that the concept was initially developed based on consideration of equivalent damage in terms of serviceability. The validity of the expression is, then, strictly restricted to the conditions under which it was derived. However, this is often ignored by pavement engineers.

The load equivalence factor, as given in Eq. (12), converts dual-tired single axles of different loads into their equivalent number of standard axles. A standard axle was defined as a dual-tired single axle of 18,000 lb (80 kN). Unfortunately, the expression is often used to estimate ESALs for axle configurations other than dual-tired single axles. For this reason, in the present research it was decided to estimate the load on different axle configurations that would cause the same damage as the standard axle. Under this assumption, two new parameters are necessary to transform different axle configurations (single-tired single axles and dual-tired tandem axles) into a number of ESALs.

The above considerations are encompassed by the *equivalent damage factor* (EDF) concept. The equivalent damage factor is defined as a number that depends only on the configuration and load characteristics of the truck. When the EDF is multiplied by the number of truck passes, the equivalent number of standard axles is obtained. This is accomplished by applying the following equation:

$$\mathrm{EDF}=\left(\frac{FA}{18\beta_{10}}\right)^{\beta_{12}}+m_1\left(\frac{SA}{18}\right)^{\beta_{12}}+m_2\left(\frac{TA}{18\beta_{11}}\right)^{\beta_{12}} \tag{13}$$

where EDF = equivalent damage factor; FA = load in kips (1,000 lb) of the front axle (single axle with single wheels); SA = load in kips of the single axle with dual wheels; TA = load in kips of the tandem axles with dual wheels; $\beta_{10,11,12}$ = parameters to be estimated; and m_1, m_2 = number of single and tandem rear axles per truck, respectively.

Equation (13) considers that trucks are configured by one front axle of load FA, a number m_1 of rear dual wheeled single axles of load SA, and a number m_2 of rear dual wheeled tandem axles of total load TA. It should be noted that only these three axle configurations were used during the AASHO Road Test. To date, these three configurations still encompass the vast majority of truck traffic configurations.

The equivalent number of standard axles is obtained by multiplying the equivalent damage factor (EDF) of each truck configuration, given by Eq. (13), by the actual number of truck passes over a given pavement section during time period t

$$\Delta N_t=n_t\ \mathrm{EDF} \tag{14}$$

where n_t = number of truck passes during period t; and ΔN_t = number of ESALs during period t.

Finally, the cumulative equivalent traffic (N_t) at time t is obtained by

$$N_t = \sum_{\ell=0}^{t} \Delta N_\ell \tag{15}$$

Final Specification of the Serviceability Model

In the preceding sections the form of the specification was given as a function of the relevant variables for a given pavement test section. In this section the full specification is given taking into account that the AASHO data set is a panel data set—time series data and cross sectional data are available simultaneously. Bearing this in mind, the complete specification becomes

$$p_{it} = p_{i0} + \sum_{\ell=1}^{t} d_i \exp\{\beta_8 G_\ell\} N_{i,\ell-1}^{\beta_9} \Delta N_{i,\ell} \tag{16}$$

where p_{it} is the serviceability at any given time, based on the initial serviceability of the section (p_{i0}) plus the summation of the changes in serviceability from the first time period after the beginning of the experiment until the period of interest. The first subscript, i, indicates the pavement test section ($i=1,...,S$), and S is the total number of pavement test sections. The second subscript, t, indicates the time period ($t=1,...,T_i$). It should be noted that the panel data set is unbalanced, i.e., not all sections are observed the same number of times. This is indicated by the subscript i in T_i, and in general, $T_i \neq T_j$ for $i \neq j$. It is important to note that in Eq. (16), the variable d_i is independent of time, and the variable G_ℓ is independent of the section. The final complete specification is

$$p_{it} = \beta_1 + \beta_2 \exp\{\beta_3 H_{1i}\} + \sum_{\ell=1}^{t} (1 + \beta_4 H_{1i} + \beta_5 H_{2i} + \beta_6 H_{3i})^{\beta_7} \exp\{\beta_8 G_\ell\} N_{i,\ell-1}^{\beta_9} \Delta N_{i,\ell} \tag{17a}$$

where $N_{i\ell} = \Sigma_{q=0}^{\ell} \Delta N_{iq}$, and ΔN_{iq} represents the traffic increment expressed in the number of ESALs for period q.

The number of ESALs is obtained by multiplying the equivalent damage factor of section i (EDF_i) by the actual number of truck passes over the pavement test section during period q. Bearing in mind the different axle truck and wheel configurations that were used during the AASHO Road Test, the final expression for ΔN_{iq} is the following:

$$\Delta N_{iq} = n_{iq}\left[\left(\frac{FA_i}{\beta_{10} 18}\right)^{\beta_{12}} + m_{1i}\left(\frac{SA_i}{18}\right)^{\beta_{12}} + m_{2i}\left(\frac{TA_i}{\beta_{11} 18}\right)^{\beta_{12}}\right] \tag{17b}$$

where n_{iq} = actual number of truck passes for section i at time period q; m_{1i}, m_{2i} = number of rear single axles and tandem rear axles per truck for each test section, respectively; FA_i = load in kips of the front axle (single axle with single wheels); SA_i = load in kips of the single axle with dual wheels; TA_i = load in kips of the tandem axles with dual wheels; and $\beta_1 - \beta_{12}$ = set of parameters to be estimated using a nonlinear optimization method.

Parameter Estimation

Nonlinear Estimation

The model described in the previous section is intrinsically nonlinear, or nonlinear in the parameters. In this sense, the term nonlinear refers to the procedure used to estimate the parameters of the specification rather than to the specification form. Thus, a general form of the nonlinear regression model can be represented as follows:

$$y_i = h(\underline{x_i}, \underline{\beta}) + \varepsilon_i \tag{18}$$

where y_i = dependent or explained variable; $\underline{x_i}$ = vector of independent or explanatory variables; $\underline{\beta}$ = vector of parameters; and ε_i = random error term; and h = a nonlinear function of $\underline{\beta}$.

If the assumption is made that the ε_i in Eq. (18) is normally distributed with mean zero and constant variance σ^2, then the value of the parameters that minimize the sum of the squared deviations will be the maximum likelihood estimators as well as the nonlinear least squares estimators. The objective function (Z_{OLS}) is given by

$$Z_{\text{OLS}}(\underline{\beta}) = \frac{1}{2}\sum_{i=1}^{n} \varepsilon_i^2 = \frac{1}{2}\sum_{i=1}^{n} [y_i - h(\underline{x_i}, \underline{\beta})]^2 \tag{19}$$

Unlike linear regression, the first order conditions for least squares estimation are nonlinear functions of the parameters. The values $\underline{b}$ of the parameters $\underline{\beta}$ obtained by minimizing Eq. (19) are referred to as the least squares estimates of $\underline{\beta}$ or the MLE estimates of $\underline{\beta}$.

Panel Data

The data set corresponding to the AASHO Road Test data set consists of panel data (time series and cross sectional data). Several approaches can be followed to undertake estimation with panel data. If the parameters of the deterioration model are believed to be constant across sections and along time, efficient parameters can be estimated by combining all data into a single regression, thereby, pooling the data.

Under this assumption, the most popular estimation technique consists of combining all time series data and cross sectional data and carrying out ordinary least squares (OLS) estimation. In this case, the intercept term is assumed to be the same for all sections. For data obtained from a controlled experiment, this assumption is not entirely unreasonable because it considers that the deterioration of all pavements is the results of the same process and only depends on the variables that are observed during the experiment. However, in most panel data sets (especially when the number of sections is large) unobserved heterogeneity is often present as a result of unobserved section-specific variables.

Unobserved heterogeneity can be dealt with in a number of ways. Some of the most commonly used techniques are: the dummy variable approach (or fixed effects approach), the error component approach (or random effects), and the random coefficients approach. The former two approaches make the assumption that the unobserved heterogeneity can be captured by means of the intercept term. The latter approach addresses the problem by assuming that one or more of the slope parameters are random rather than constant. Only the random effects approach is used in this research because it is considered more appropriate.

The random effects approach (or error components approach) makes the assumption that the intercept term is randomly distributed across cross sectional units. That is, instead of assuming that there is one intercept term β_{1i} for each section (as the fixed effect approach does), it assumes that $\beta_{1i} = \beta_1 + u_i$, where u_i is a random disturbance which is a characteristic of the section i that remains constant through time. Thus, the regression model becomes

Table 1. Parameter Estimates and Asymptotic (Asym.) t Values for Ordinary Least Squares (OLS) and Random Effects (RE) Estimation

Parameter	OLS estimate	Asym. t value	RE estimate	Asym. t value
β_1	4.45	57.1	4.24	165.4
β_2	−1.47	−16.5	−1.43	−8.9
β_3	−0.555	−6.2	−0.856	−8.4
β_4	2.28	14.1	1.39	17.6
β_5	0.775	10.8	0.329	14.4
β_6	0.546	11.3	0.271	15.2
β_7	−2.67	−29.5	−3.03	−35.2
β_8	−0.186	−49.0	−0.173	−47.7
β_9	−0.473	−39.8	−0.512	−49.5
β_{10}	0.790	22.3	0.552	29.6
β_{11}	1.72	101.2	1.85	109.4
β_{12}	3.57	46.0	4.15	54.6

$$y_{it}=h(\underline{\beta},\underline{x}_{it})+u_i+\varepsilon_{it} \tag{20}$$

The generalized least squares estimator can be used when the variance of the error components σ_ε^2 and σ_u^2 are known. For the experiment under consideration, the components σ_ε^2 and σ_u^2 are unknown. Hence, feasible generalized least squares has to be applied to estimate the values of the vector of parameters $\underline{\beta}$ (Greene 2000).

Estimation Results

The parameters of the serviceability deterioration model [Eq. (17)] were estimated using both the ordinary least squares (OLS) and the random effects (RE) approach. The estimated parameters and the asymptotic t values are given in Table 1. The estimates were obtained using only the data originated from the AASHO Road Test. Table 1 shows that all the parameter estimates are statistically significantly different from zero at a 5% level and all the parameters have the expected sign.

The estimate of the standard error of the OLS regression is $\hat{\sigma}_\varepsilon=0.248$ PSI, which is approximately half of the value of the standard error of the original linear model developed during the original analysis of the AASHO Road Test data. It should be emphasized that this reduction in the error was achieved using the same data source as in the original study, as well as the same number of explanatory variables. The improved accuracy is the result of a better-specified model due to the use of a nonlinear specification.

Table 1 illustrates the difference in the estimates obtained between the OLS approach and the RE approach. Although the differences in some of the estimated parameters are relatively small, they could be very significant, as is the case of the exponent of the power law. This aspect is discussed in detail in the next paragraphs. The estimates of the variance of the error components for the random effect approach were 0.142 and 0.126 for the overall error (ε_{it}) and the section specific error (u_i), respectively. Both values are of the same order of magnitude, indicating that heterogeneity should not be ignored.

The parameters for the determination of the equivalent layer thickness (β_4, β_5, and β_6) are different from the parameters that were developed during the original analysis of the AASHO Road Test for the determination of the thickness index (HRB 1962). However, the relative values are comparable. For instance, in the new model the ratios β_4/β_5 and β_5/β_6 are approximately 4 and 1.2, respectively. The equivalent ratios obtained from the original model are 3 and 1.3, respectively. It is important to note that the concept of equivalent thickness is applicable within reasonable ranges of surface, base and, subbase thicknesses.

The equivalent thickness is important in the specification because it dictates the rate at which deterioration (in terms of serviceability loss) progresses. This is illustrated graphically in Fig. 2. As expected, the rate of deterioration decreases as the strength of the pavement increases. The rate of serviceability loss depends also on the cumulative traffic. As can be seen from Fig. 2, the rate of deterioration decreases with cumulative traffic. This is represented by the parameter β_9 in the specification, whose sign is negative. It should be noted that the parameter β_9 is not intended to capture the effect of dynamic loads but processes such as aging and densification of the materials.

Other parameters that deserve special attention are the parameters corresponding to the aggregate traffic specification. That is, β_{10}, β_{11}, and β_{12}. These parameters facilitate the estimation of the *equivalent damage factors* (EDFs) and the determination of the equivalent axle loads for different axle configurations. The

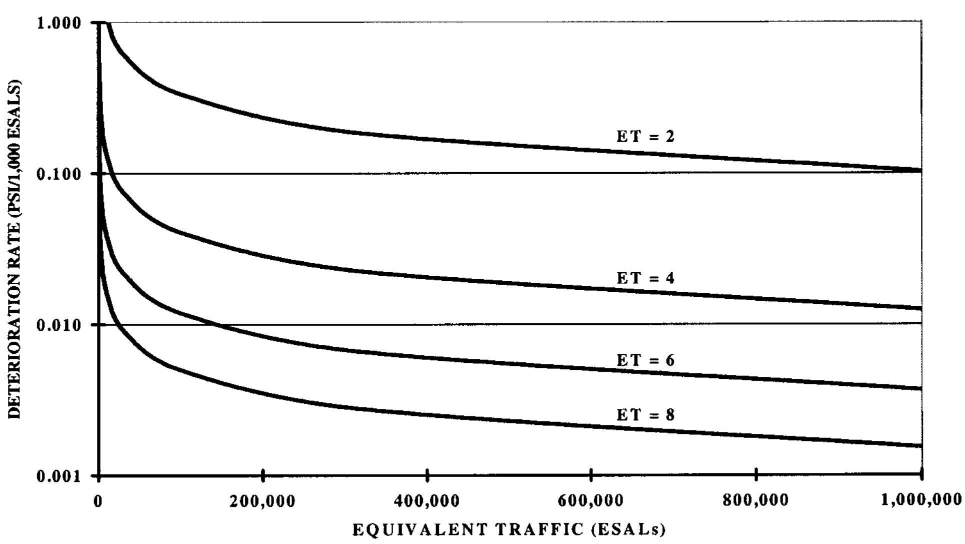

Fig. 2. Deterioration rate as function of strength and traffic

equivalent axle loads are the loads on the different axle configurations that would cause the same loss of serviceability as the standard axle. A single axle with dual wheels and an axle load of 18 kips (80 kN) was considered the standard axle. Therefore, the axle load corresponding to an EDF of one determines the equivalent axle load for the given configuration.

The estimated equivalent load for a single axle with single wheels is approximately 10,000 lb., while the equivalent load for a tandem axle with dual wheels is about 33,000 lb, which is consistent with findings at the AASHO Road Test. These values are obtained by multiplying the parameters β_{10} and β_{11} by the standard axle load (18,000 lb). Thus, it is estimated that a 10 kip single axle with single wheels would cause the same damage to a road (in terms of serviceability) as a standard 18 kip single axle with dual wheels. Similarly, a tandem axle of 33 kip would cause as much damage as the standard axle.

Minnesota Road Research Project

To update the initial model by applying joint estimation, a second data source was incorporated. This data source is the Minnesota Road Research Project (MnRoad). The facility is located parallel to Interstate 94 (I-94) in Otsego (Minnesota),—approximately 40 miles (65 km) northwest of the Minneapolis-St. Paul metropolitan area. The test setup comprises both experimental test sections and in-service pavement sections (field sections). The field data set consists of 3 miles (4.8 km) of two-lane interstate (also referred to as the High Volume facility). The experimental data set consists of a 2.5 miles (4.0 km) closed-loop test track (also referred to as the Low Volume facility).

The estimated traffic on Interstate 94 is about 14,000 vehicles per day. This traffic is periodically diverted onto the High Volume facility where there are 23 test cells that are heavily instrumented. These test cells comprise flexible and rigid pavements. The instrumentation monitors and records the response and performance of the pavements subjected to actual highway traffic. This feature is unique to MnRoad and makes the data set optimally suited for the estimation of road performance under actual highway traffic conditions and experimental traffic simultaneously. The High Volume facility is also referred to as the Mainline Experiment.

The Low Volume facility consists of 17 test cells that include Portland cement concrete (PCC), asphalt cement concrete (AC), and various unpaved surfaces. The sections were constructed in late summer 1993 and testing has been conducted since then. A weather station that is located at the MnRoad project site routinely collects environmental data. During the winter and early spring months, the depth of frost penetration is monitored using soil resistivity probes. The low volume facility is subjected to controlled experimental loading consisting of a single vehicle circling the two-lane test track. The inside lane is trafficked four days a week with a legally loaded truck whose total weight is 79,500 lb (353 kN); while the outside lane is trafficked only one day a week with a 25% overloaded truck whose total weight is 102,000 lb (453 kN). Both low and high volume facilities are instrumented with weight-in-motion and automatic vehicle classification systems. Although weight and classification errors are expected, it was assumed that these errors are random.

The interstate portion of the test facility has been divided into two parts, referred to as the 5-Year and the 10-Year Mainline. These interstate sections have been designed for an estimated 5- and 10-year design life, respectively. Both the 5- and the 10-year mainline sections have PCC and AC test cells. However, only the data corresponding to the flexible pavement cells are used for the estimation of the deterioration models in this research. Twenty-two cells have asphalt concrete surface, and all of them are 150 m long. The cells corresponding to the 5-Year Mainline (numbered 1–4) had a surface thickness ranging from 5.75 to 9.75 in. (145–295 mm) while the cells corresponding to the 10-Year Mainline (numbered 14–23) had a surface thickness ranging from 7.75 to 25.75 in. (195–645 mm). The aggregate base for these cells had a maximum thickness of 37 in. (925 mm). The test cells on the low traffic facility corresponding to flexible pavements (numbered 24–31) had thicknesses ranging from 3 to 14 in. (75–350 mm), while the corresponding aggregate base had a maximum thickness of 12 in. (300 mm). Four different material types were used for the untreated granular base and subbase layers.

One of the main advantages of the MnRoad project data set, compared to any previous experiment, is that it combines both experimental data (Low Volume road) and field data from in-service pavement sections subjected to actual highway traffic (Mainline Experiment). This is perfectly suited to the objective of this paper and can be fully exploited by the application of joint estimation. Another advantage is that the field data consisted of specially built pavement sections, and thus did not suffer from the problem of endogeneity in the explanatory variables.

Joint Estimation Method

Assuming two different data sources [experimental (E) and field data (F)], the joint estimation approach can be formulated as follows:

$$\begin{aligned} r_E &= h(\theta, x, \theta_E, x_E) + \varepsilon_E \\ r_F &= h(\theta, x, \theta_F, x_F) + \varepsilon_F \end{aligned} \tag{21}$$

where r_E, r_F = riding quality from the experiment and the field, respectively; x = explanatory variables shared by the experimental and field data sources; θ = vector of parameters shared by both models; x_E = vector of variables unique to the experimental model; θ_E = vector of parameters corresponding to x_E; x_F = vector of variables unique to the field model; θ_F = vector of parameters corresponding to x_F; and ε_E, ε_F = random error terms for the experimental and field model, respectively.

In general, parameter estimation results from the optimization of a particular objective function with respect to that set of parameters. In the case of joint estimation, the objective function is the sum of the objective functions of the individual data sources. This summation is reasonable under the assumption that the error terms of the two data sources [Eq. (21)] are uncorrelated. For the AASHO Road Test data set and the MnRoad Project data the error terms can be safely assumed to be uncorrelated.

Archilla and Madanat (2001) carried out the first application of joint estimation within the context of pavement performance. The authors identified the main advantages of using the technique as follows:

1. Identification. By incorporating a new field data source, variables that were not observed during the experiment can now be observed in the field and their effect can be incorporated into the specification and estimated from the pooled data.
2. Bias correction. It may be reasonable to expect that the model estimated with the experimental data set could produce biased parameter estimates for the prediction of the performance of field sections. Joint estimation enables such potential biases to be estimated and corrected. For instance, this can be done by applying an additive or a multiplicative

bias correction factor. In the case of a multiplicative factor, it can be hypothesized that for some k's (with $k<K$ = number of parameters): $\beta_k^E=\lambda_k\beta_k^F$. By applying joint estimation, the true parameters λ_k and β_k can be estimated simultaneously with the rest of the parameters.
3. Efficiency. If the deterioration process described by the set of Eq. (21) is believed to be the same for the different data sources, efficient parameter estimation cannot be achieved by estimating the parameters of the equations separately. Only joint estimation with the pooled data would produce efficient parameter estimates.

It is reasonable to expect that the specification of the deterioration model based on the second data source (MnRoad Project) will be different than the one based on the AASHO Road Test data. Although the reasons for riding quality deterioration are the same, the data from MnRoad contain a number of variables that were not observed during the AASHO Road Test.

Measurement Error Model

The necessary condition for the application of joint estimation is that both models represented by Eqs. (21) have to have at least one parameter in common. This condition is satisfied because the AASHO Road Test and the Low Volume Road of the MnRoad Project are conceptually very similar and both make use of controlled experimental traffic. The main difference lies in the fact that the layer materials used at AASHO and at MnRoad have different strength characteristics. Hence, the shared parameters make joint estimation feasible, while dissimilar parameters enable the identification of the effect of new variables.

A second necessary condition for the applicability of joint estimation is that the observed dependent variable be equivalent. Riding quality observations from the AASHO Road Test and the MnRoad Project are, at first sight, incompatible. During the AASHO Road Test, riding quality was assessed as serviceability by means of the Present Serviceability Index (PSI). At MnRoad Project roughness is assessed by means of the International Roughness Index (IRI). An empirical relationship between IRI and serviceability was developed during the International Road Roughness Experiment conducted in Brazil in 1982 (Sayers et al. 1986). That relationship is

$$r=5.5\ln\left(\frac{5.0}{p}\right) \tag{22}$$

where r = roughness in m/km IRI, and p = serviceability in PSI.

The empirical relationship given in Eq. (22) is very accurate for values of roughness below 12 m/km. This relation is especially valid for the serviceability observed during the AASHO Road Test, where 95% of the serviceability is explained by the variance of the surface profile (Haas et al. 1994).

The simultaneous estimation of bias in the parameters and the estimation of the measurement error model are not feasible when only two data sets are available. However, by jointly estimating the deterioration model with AASHO and MnRoad data, three different data sets are in fact used. The procedure is as follows: the model is specified in terms of roughness based on the AASHO Road Test. Since roughness was not observed during the AASHO Road Test, the observed serviceability [transformed by means of Eq. (22)] is used as the dependent variable. An error is thus introduced into the model. This error is referred to as the measurement error (Humplick 1992). This measurement error cannot, in general, be determined and produces parameter estimates that are unbiased but not efficient. However, by incorporating a second data source (MnRoad Low Volume facility) and applying joint estimation, the magnitude of the measurement error can be estimated as follows. From AASHO the following relationship can be established:

$$y_1=h(X,\theta)+\varepsilon_1 \tag{23}$$

where y_1 is the observed roughness (in m/km IRI) during the AASHO Road Test. Accordingly, from MnRoad

$$y_2=h(X,\theta)+\varepsilon_2 \tag{24}$$

where y_2 is the observed roughness at the MnRoad Project. The assumption is made that the error terms ε_1 and ε_2 are both normally distributed with zero mean $(E(\varepsilon_1)=E(\varepsilon_2)=E(\varepsilon)=0)$ and constant variance $(\sigma_1^2=\sigma_2^2=\sigma^2)$. However, during the AASHO test y_1 (roughness) was not observed but y_1^* [which is actually a function of the observed serviceability given by Eq. (22)], so

$$y_1^*=y_1+\varepsilon^* \tag{25}$$

The error term ε^* is also assumed to be normally distributed with zero mean and constant variance (σ^{*2}). The final assumption is that the independent explanatory variables (X) in Eq. (23) are uncorrelated with ε^*. Under this assumption the final joint model is

$$y_{1,2}=h(X,\theta)+(\varepsilon+\varepsilon^*) \tag{26}$$

Under these assumptions, both error terms (ε and ε^*) are present when considering the AASHO Road Test data, while only one component (ε) is present when considering the MnRoad project data.

Specification of the Joint Model

The joint model specification is based on the specification of the serviceability model described earlier, and the relationship given by Eq. (22). However, the joint specification for riding quality is given in terms of roughness rather than serviceability as in the model described earlier.

Furthermore, it should be noted that in this new specification, the pavement strength is given by the *equivalent asphalt thickness* (EAT) as opposed to the equivalent thickness used in Eq. (17). The EAT expresses the total strength of the pavement in terms of the equivalent thickness of asphalt concrete, whose strength characteristics are those of the AC mixture used at the AASHO Road Test. Six different layers are now considered in the specification. The first three correspond to the surface, base, and subbase layers used at the AASHO test sections, while the last three correspond to the surface, base, and subbase layers used at MnRoad Project.

Taking into account these two aspects, the specification for the roughness is given by

$$r_{it}=\theta_1 e^{\theta_2 H_{1i}}+\sum_{\ell=1}^{t}\theta_3(1+\mathrm{EAT}_i)^{\theta_9}e^{\theta_{10}G_\ell}N_{i,\ell-1}^{\theta_{11}}\Delta N_{i,\ell} \tag{27a}$$

$$\mathrm{EAT}_i=H_{1i}+\theta_4H_{2i}+\theta_5H_{3i}+\theta_6H_{4i}+\theta_7H_{5i}+\theta_8H_{6i} \tag{27b}$$

where r_{it} = roughness (in m/km IRI): EAT = equivalent asphalt thickness (relative to the asphalt concrete used during the AASHO test); H_j = layer thickness [when one set of layer thickness (e.g., H_1, H_2, H_3) takes nonzero values, the elements of the other set (e.g., H_4, H_5, H_6) take zero values]; G = frost gradient; and θ_j = parameters to be estimated.

Where $N_{i\ell}=\Sigma_{q=0}^{\ell}\Delta N_{iq}$, and ΔN_{iq} represents the traffic increment in ESALs for period q. In the cases of AASHO and MnRoad Low Volume facility, the number of ESALs is obtained by multiplying the equivalent damage factor of section i (EDF_i) by the actual number of truck passes over the pavement test section during period q. Thus, the expression for ΔN_{iq} is the following:

$$\Delta N_{iq}=n_{iq}\left[\left(\frac{FA_i}{\theta_{12}18}\right)^{\theta_{14}}+m_{1i}\left(\frac{SA_i}{18}\right)^{\theta_{14}}+m_{2i}\left(\frac{TA_i}{\theta_{13}18}\right)^{\theta_{14}}\right] \tag{27c}$$

where n_{iq}=actual number of truck passes for section i at time period q; m_{1i}, m_{2i}=number of rear single axles and tandem rear axles per truck for each section, respectively, FA_i=load in kips of the front axle (single axle with single wheels); SA_i=load in kips of the single axle with dual wheels; and TA_i=load in kips of the tandem axles with dual wheels.

Traffic on the High Volume facility was not experimental, but it was actual highway traffic diverted from Interstate 94. Unfortunately, the raw traffic data information from this portion of I-94 was not available. Traffic counts and load information were automatically converted into ESALs by MnRoad personnel. The determination of the number of ESALs was based on the AASHO approach, which takes into account the axle configuration and the pavement strength. Therefore, in the case of the MnRoad High Volume Road, the number of ESALs is determined by converting the observed ΔN_{iq} by means of a multiplicative bias correction factor as follows:

$$\Delta N_{iq}=\theta_{15}\Delta \mathrm{ESAL}_{iq}^{M} \tag{27d}$$

where $\Delta ESAL_{iq}^{M}$ is the observed number of ESALs for section i and period q at the MnRoad High Volume Road facility. The estimation of $\Delta ESAL_{iq}^{M}$ is based on the AASHO approach (AASHTO 1993), while the determination of ΔN_{iq} is based on the concept of the equivalent damage factor introduced in this paper [Eq. (27c)]. The AASHTO approach assumes different standard axle loads and different exponents from the ones estimated by applying Eq. (27c). However, for a given observed traffic spectrum, a multiplicative factor is sufficient to capture the difference.

Estimation of the Joint Model

The parameters of the specification were estimated using the random effects approach, taking into account the measurement error model. The estimated parameters and their asymptotic statistics are given in Table 2. The estimated variances of the two error components are $\hat{\sigma}_{\varepsilon}^2=0.380$ (overall error) and $\hat{\sigma}_{u}^2=0.368$ (section specific error). Statistical testing (through Lagrange Multipliers, LM) was carried out to determine the extent of the unobserved heterogeneity. The LM was significantly different from zero at a 5% level so the unobserved heterogeneity cannot be ignored.

The estimate of the error of the measurement error model is $\hat{\sigma}_{*}^2=0.793$, which is of the same order of magnitude as the regression error. Thus, this measurement error cannot be ignored. If the measurement error were ignored, some of the estimated parameters would not be significantly different from zero at the 5% significance level.

The estimated standard error of the regression ($\sqrt{\hat{\sigma}_{\varepsilon}^2+\hat{\sigma}_{u}^2}$) is 0.865 m/km IRI. This nonlinear model fits the observed data of the AASHO Road Test better than original AASHO linear regression. The improved accuracy of the nonlinear model developed in this research is attributed to an appropriate specification form and the use of adequate estimation techniques. It should be emphasized that both models made use of the same number of explanatory variables. The improved accuracy can also be seen graphically. Observed and predicted deterioration of two different pavement sections are illustrated in Figs. 3 and 4. It should be noted that the data of the AASHO sections represented in Figs. 3 and 4 were not used for the estimation of the parameters. The data available from MnRoad was limited so all data were used in the estimation. As data from new experiments become available, the new data could be used to reassess the accuracy of the model.

A relatively weak pavement section subjected to light traffic is represented in Fig. 3. In this case, both models (the original linear AASHO model and the model developed in this research) predict roughness well. However, when heavier traffic is applied to the pavement section, the nonlinear model developed in this research predicts substantially better than the original linear model (Fig. 4).

Another important aspect of the nonlinear model is its ability to predict the distinctive deterioration rate characteristic of the critical thawing period. Under this critical condition the deterioration of the pavement section takes place at a significantly higher rate. This can be observed in Fig. 3 and, more dramatically, in Fig. 4. The absence of heteroskedasticity can also be appreciated in the figures.

Table 2. Parameter Estimates of Joint Model and Corresponding t Values

Parameter	Estimated value	t value
θ_1	1.58	45.8
θ_2	−0.126	−28.0
θ_3	0.787	15.7
θ_4	0.237	56.3
θ_5	0.204	54.5
θ_6	1.82	22.7
θ_7	0.288	8.6
θ_8	0.236	11.7
θ_9	−3.77	−70.2
θ_{10}	−0.157	−77.3
θ_{11}	−0.374	−50.7
θ_{12}	0.523	45.2
θ_{13}	1.85	170.5
θ_{14}	3.85	92.9
θ_{15}	4.27	4.4

Discussion of Results of the Joint Model

Several of the parameter estimates of the joint model (roughness model) given in Table 2 have an equivalent counterpart in the serviceability model described earlier. It is important to note that the corresponding equivalent parameters of both models have very similar estimated values. For instance, the parameters corresponding to the aggregate traffic specification in the serviceability model are β_{10}, β_{11}, and β_{12}, while the corresponding parameters in the roughness model are θ_{12}, θ_{13}, and θ_{14}. The estimated values for these parameters in both models are given in Table 3.

The largest difference in the estimated values of these three parameters is approximately 7%. This corresponds to the exponent of the equivalent traffic. Although the difference seems to be negligible, it may have important implications when determining the design ESALs for a given pavement section. The value 4.15

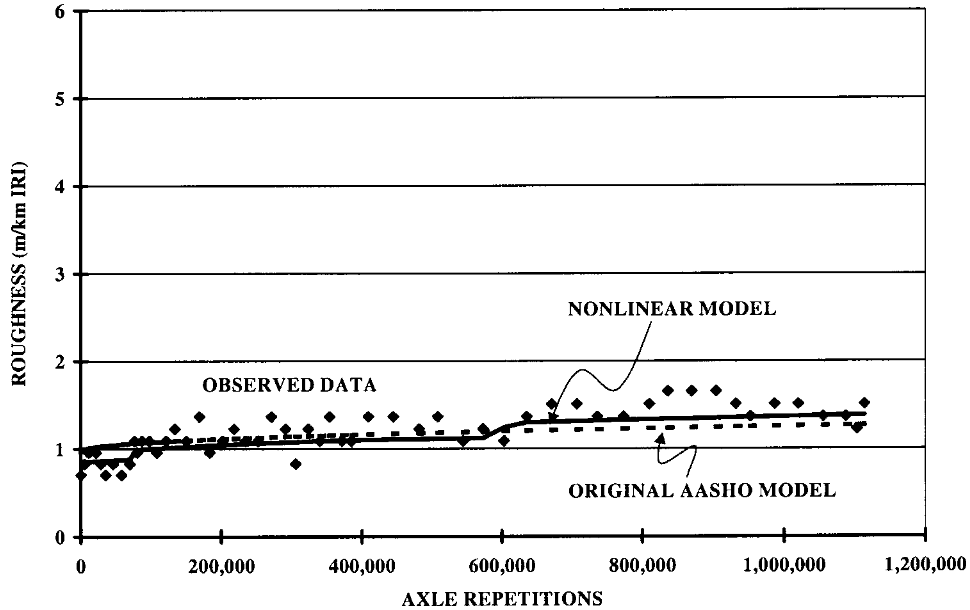

Fig. 3. Observed versus predicted performance by linear and nonlinear models for pavement section not used in estimation sample (6,000 lbs single rear axle)

allocates more weight to the higher traffic axle loads (greater than 18 kip), while the value 3.85 places more weight on the lighter traffic axle loads (smaller than 18 kip). A smaller exponent does not necessarily imply less equivalent traffic.

Another important difference between the two models relates to the formulation of the equivalent thickness. In the serviceability model, the equivalent thickness (ET) is expressed relative to the subgrade protection against loss in serviceability. In the roughness model, the equivalent asphalt thickness (EAT) is expressed in terms of the effectiveness of the asphalt layer to protect the pavement against damage due to roughness. Hence, the absolute values of the parameters β_4, β_5, and β_6 (in the serviceability model) bear no direct relationship to the absolute value of parameters θ_4 and θ_5. (in the roughness model). However, their relative values β_5/β_4 and β_6/β_4 are 0.237 and 0.195, which compare favorably with the estimated values for θ_4 and θ_5, respectively.

Joint estimation allows the estimation of the layer strength coefficients for materials that were not available during the AASHO Road Test. Three new strength coefficients were estimated (θ_6, θ_7, and θ_8) which correspond to the asphalt surface, base, and subbase materials used for the construction of the MnRoad test sections (Table 4). In the MnRoad Project, two asphalt binders were used for the surface layer, and four different un-

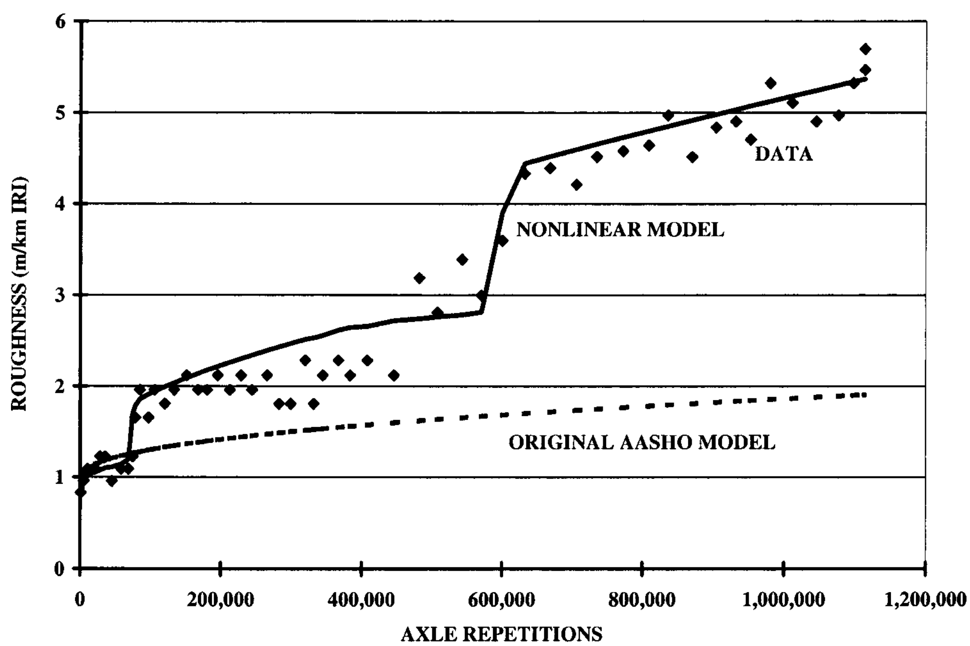

Fig. 4. Observed versus predicted performance by linear and nonlinear models for section not used in estimation sample (24,000 lbs tandem rear axle)

Table 3. Comparison of Corresponding Parameters (for determination of equivalent traffic) of Serviceability and Roughness Models

Serviceability model		Roughness model	
Parameter	Estimate	Parameter	Estimate
β_{10}	0.552	θ_{12}	0.523
β_{11}	1.85	θ_{13}	1.85
β_{12}	4.15	θ_{14}	3.85

treated granular materials for the base and subbase layers (Class 3 to Class 6 according to MnRoad specifications). However, the available data to date do not allow the estimation of one coefficient per material type. Therefore, it was decided to group the materials together following current practice at the Minnesota Department of Transportation.

The two asphalt mixtures were grouped into one material type. Class 5 and Class 6 untreated granular materials were grouped into base quality material, and Class 4 and Class 3 materials were grouped together as subbase quality materials. The estimated parameters for these three material groups are 1.82, 0.288 and 0.236 (Table 4). According to these estimates, the asphalt mixtures used in MnRoad are 82% more effective than the asphalt mixture used in the AASHO test in terms of protecting the pavement structure against roughness damage. Accordingly, 1 in. of base and subbase quality materials is approximately 29 and 24% as effective as 1 in. of the original asphalt mixture. These results indicate that the asphalt mixture used in MnRoad is significantly superior to that used in the AASHO Road Test. The materials used for the untreated base and subbase layers in MnRoad are also of superior quality compared to those used at the AASHO test. The relative contributions are 29 and 24% as compared to 24 and 20%, respectively, of the materials used at the AASHO test. Both differences are statistically significant at a 10% level.

The estimation of a multiplicative bias parameter (θ_{15}) to correct for the ESALs determined at High Volume facility of MnRoad is made possible by the joint estimation technique. This value indicates that the current method to estimate ESALs in the

Table 4. Comparison of Corresponding Layer Strength of Materials Used at AASHO Road Tests and at MnRoad Project

AASHO road test			MnRoad project		
Parameter	Layer	Estimate	Parameter	Layer	Estimate
(*)	Surface	1.00(*)	θ_6	Surface	1.82
θ_4	Base	0.237	θ_7	Base	0.288
θ_5	Subbase	0.204	θ_8	Subbase	0.236

(*) Note: the estimated values of the layer strength parameters are relative to the asphalt concrete mixture used at the AASHO Road Test.

High Volume facility underestimates the equivalent traffic. This discrepancy is partially attributed to the fact that the current procedure for the estimation of equivalent traffic is based on the AASHO approach, which does not necessarily apply. In addition, the current AASHO procedure is believed to underestimate equivalent traffic, especially when the traffic spectrum is composed of a large proportion of light traffic. The difference is believed to be too large and further research is recommended in this area.

According to the estimated model, the rate at which the roughness of a given pavement section increases is a function of the equivalent asphalt thickness of the pavement structure (EAT), the gradient of frost penetration (G), and the cumulative traffic (N) that has been applied to the section. This relationship is represented graphically in Fig. 5 for three different equivalent asphalt thicknesses (4, 6, and 8 in.) and three different frost gradients (-2, 0 and $+2$ in. per day). It can be observed that as the cumulative traffic increases, the roughness rate decreases. It can also be observed that the roughness rate decreases as the frost gradient increases, which is typical in the winter freezing period. On the other hand, the roughness rate increases as the frost gradient decreases.

The most important characteristics of the joint model can be summarized as follows:

1. The joint model was developed primarily for the management of the road network. Within a pavement management

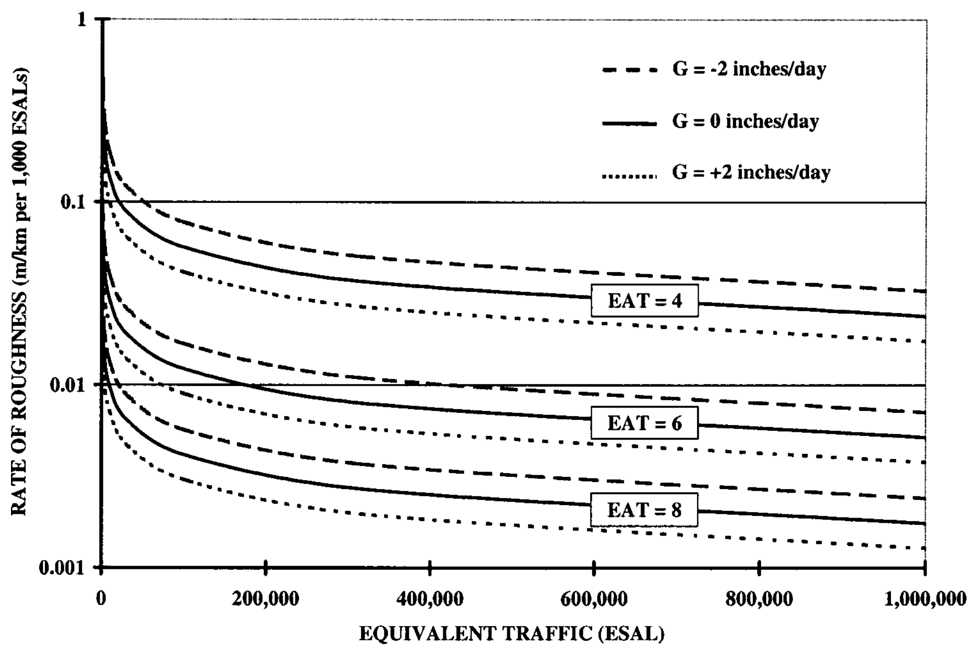

Fig. 5. Variation of rate of roughness increase as function of traffic, pavement strength, and environmental conditions

context, predictions are usually required only for the following time period. Hence, the model predicts roughness incrementally. Thus, roughness at time t is the sum of predicted roughness increments over time intervals Δt.

2. The estimated exponent for the equivalent traffic determination (3.85) indicates that currently used values (4.0–4.2) overestimate the equivalent traffic of the higher load ($>$18,000 lb) classes, but underestimate the equivalent traffic of the lower load classes ($<$18,000 lb). This is important since most highway traffic is mainly composed of light traffic.
3. The specification for aggregate traffic allows the determination of equivalent axle loads for different configurations. Equivalent loads were estimated for single axles with single wheels, and for tandem axles with dual wheels. The equivalency is expressed relatively to the deterioration effect on roughness of an 18,000 lb dual-tired single axle. The estimated values are 9,400 and 33,000 lb, respectively. Thus, the practice of using the same equivalent load for different axle configurations (e.g., single axles with dual or single tires) should be avoided to prevent gross estimation errors of equivalent traffic. The equivalent loads could be used for the allocation of cost responsibilities for pavement deterioration to the different axle configurations.
4. The specification of pavement strength in terms of the equivalent asphalt thickness (relative to the asphalt mixture used in the AASHO Road Test) allows for the determination of the relative contribution of the various materials to the overall pavement strength. Joint estimation allowed not only for the estimation of the relative contribution of the materials available at the time of the AASHO Road Test, but also for the estimation of the relative strength of the materials used at the MnRoad Project.
5. Another unique feature of the roughness prediction model is the estimation of the effect of the initial thickness of the asphalt surface on the value of the initial roughness. The estimated results show that the initial roughness decreases as the thickness of the asphalt surface increases, as was observed in the data.

Conclusions and Recommendation

This research has highlighted the benefits of using joint estimation for the development of pavement performance models. A nonlinear serviceability model was developed using the same data set and the same variables as the equivalent existing linear model. The prediction error of the new nonlinear model was, however, half that of the existing model. By halving the prediction error, highway agencies in charge of the management of the road network can obtain significant budget savings by timely intervention and accurate planning.

The serviceability model was then updated to estimate riding quality in terms of roughness expressed in m/km IRI. It should be noted that during the estimation, no restrictions were imposed on the parameter values, i.e., no traditionally used values were assumed. All the parameters of the updated model were jointly estimated with the data from the AASHO Road Test and the MnRoad Project. Joint estimation allows for the full potential of both data sources to be exploited. In the context of this paper, the main advantages of joint estimation were:

1. The effect of variables not available in the first data source were identified and quantified;
2. The parameter estimates had lower variance because multiple data sources were pooled;
3. Bias in the parameters of the experimental model were identified and corrected; and
4. Different measurements of the same property were incorporated by using a measurement error model.

Like any other deterioration model, the model developed in this research is only an approximation of the actual physical phenomenon of deterioration. There is a prediction error associated with the model. However, unlike deterministic predictions characteristic of most mechanistic approaches, this error can be estimated to assess the uncertainty in the predictions. Although the prediction capabilities of the developed models are superior to most existing models, a number of limitations have been identified and should be further researched.

The two data sources used for the joint estimation are from the states of Illinois and Minnesota. Environmental conditions at these locations are similar, especially in terms of weather and soil conditions. The developed model is thus conditional on such conditions, and might produce biased predictions in other states or regions of markedly different characteristics. A possible approach to overcome this limitation would consist of obtaining another data source (corresponding to a different region) and updating the models by applying joint estimation once again. The data collected as part of the long-term pavement performance studies of the Federal Highway Administration could also be ideal for this purpose. By using in-service pavement data, a large number of new variables could be incorporated into the deterioration model, and important potential biases could be determined and corrected. The information contained in pavement management systems (PMS) of various states could also be used; however, state PMS data alone tend to produce models with few significant variables. It is in these cases that joint estimation could become a viable and very valuable approach.

Finally, these limitations are a characteristic of the specific model. However, this research ultimately aimed at showing the feasibility and advantages of using joint estimation to develop pavement deterioration models rather than the advantages of the model itself. As indicated above, most of these limitations can be overcome by repeatedly applying joint estimation to more data sources.

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