Modeling pavement performance by combining field and experimental data

by

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Abstract

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

The goal of this research was to develop a methodology for developing accurate pavement deterioration models to be used primarily for the management of the road infrastructure. The loss of the riding quality of the pavement was selected as the performance indicator. Two measures of riding quality were used: serviceability (Present Serviceability Index, PSI) and roughness (International Roughness Index, IRI).

An acceptable riding quality is important for both the road user and the goods being transported. Riding quality affects the comfort of the user for whom the road is provided, and the smoothness with which goods are moved from one point to another. The vehicle

operating costs and the costs of transporting goods increase as the road riding quality deteriorates. These costs are often one order of magnitude more important than the cost of maintaining the road to an acceptable level of service.

The initial incremental models developed in this dissertation predict serviceability as a function of material properties, pavement structural characteristics, traffic axle configuration, axle load, and environmental variables. These models were developed applying nonlinear estimation techniques using an experimental unbalanced panel data set (AASHO Road Test). The unobserved heterogeneity among the pavement sections was accounted for by using the random effects approach.

The serviceability models were updated using joint estimation with a field panel data set (MnRoad Project). The updated model estimates riding quality in terms of roughness. This was possible by applying a measurement error model to combine both data sources.

The main contribution of this research is not the development of a deterioration model itself, but rather the demonstration of the feasibility of using joint estimation and its many advantages, such as: (i) identification and quantification of new variables, (ii) efficient parameter estimates, (iii) bias identification and correction, and (iv) use of a measurement error model to combine apparently incompatible data sources.

To my wife, Jolanda,

to my parents, Cesar and Juanita,

and to my brothers and sisters, Guillermo, Marina, Jose, Carolina and especially to Fernando, who is no longer with us.

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Chapter 1: Introduction and Objectives

1.1 Background

A road pavement continuously deteriorates under the combined actions of traffic loading and the environment. The ability of the road to satisfy the demands of traffic and the environment over its design life is known as ***performance***. The most common indicators of pavement performance are: fatigue cracking, surface rutting, riding quality, and skid resistance. The change in the value of these performance indicators over time is referred to as ***deterioration***.

This research focuses on a methodology to develop models to predict the deterioration of the riding quality of road pavements as a function of traffic characteristics, pavement properties and environmental conditions. Hence, pavement performance is herein defined as the history of the deterioration of the riding quality.

Riding quality, per se, is a fairly subjective measure of performance. It not only depends on the physical characteristics of the pavement (surface unevenness) and the mechanical properties of the vehicle (mass and suspension), but also on the users' perception of acceptable pavement quality. For instance, at any point in time, the riding quality of a given pavement section can be perceived differently by different road users. Moreover, riding quality expectations of a given user can be different at different points in time.

The first comprehensive effort to establish an objective indicator of pavement performance was made in the late 1950s. Until that time, inadequate attention had been paid to the evaluation of pavement performance: a pavement was considered to be either satisfactory or unsatisfactory (Haas et al, 1994).

The Present Serviceability Index (PSI) was developed in the early 1960s and constituted the first comprehensive effort to establish performance standards based upon considerations of riding quality (Carey and Irick, 1960; Highway Research Board, 1962). A panel of highway users from different backgrounds evaluated seventy-four flexible pavement sections and rated them on a five-point discrete scale (0 for poor, 5 for excellent). This rating was averaged for each section converting the discrete rating into a continuous rating referred to as the Present Serviceability Rating (PSR).

The PSR was found to correlate highly with longitudinal profile variation in the wheelpath (slope variance), and to a lesser extent with rut depth, cracking and patching. Ninety five percent of the change of the PSR could be explained by the variation of the slope variance (Haas et al, 1994). Therefore, an empirical equation was developed to determine serviceability as a function of surface slope variance, cracking, rutting and patching measured in the pavement section. The serviceability value estimated with this equation was called the Present Serviceability Index (PSI). Thus, serviceability became the first objective measure of performance based upon considerations of riding quality.

Subsequently, other studies have been carried out to establish alternative measures of riding quality. Some of the most well-known concepts that have been developed are: the Riding Comfort Index (RCI) (CGRA, 1965), the International Roughness Index (IRI) (Gillespie et al, 1980; Sayers et al, 1986), and the Pavement Condition Index (PCI) (Shahin and Kohn, 1979). To date, the International Roughness Index has enjoyed the broadest application and has been adopted as a standard for the Federal Highway Performance Monitoring System (FHWA, 1987).

The IRI is a summary statistic of the surface profile of the road and is computed from the surface elevation. It is defined as the average rectified slope, which is the ratio of the accumulated suspension motion to the traveled distance obtained from a mechanical model of a standard quarter car traveling over the road profile at 80 km/h (Huang, 1993).

1.2 Research goal and objectives

The goal of this research is to develop a methodology for developing sound pavement riding quality deterioration models to be used primarily for the management of the road infrastructure. Ideally, these performance models could also be used for the design and analysis of flexible pavements. 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). This is especially important since the road infrastructure network is usually the single most expensive asset owned by a local government.

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.

To achieve the above-mentioned goal the following objectives should be accomplished for this research:

(i) The first objective is to ***development of accurate deterioration models*** for predicting the riding quality of flexible pavements. These models should be based on the most reliable and comprehensive experimental data sources available. The models should incorporate the effects of the structural characteristics of the pavement, as well as the characteristics of the traffic and environmental conditions. The specification of the model should be based on sound engineering principles, and the estimation of the models should be carried out following rigorous statistical techniques.

(ii) The second objective is to ***transfer the deterioration models*** developed with experimental data to actual traffic and environmental conditions. Transferability (or model updating) will be accomplished by joint estimation of the models using experimental and field data. By jointly estimating the parameters of the models, the effect of new variables can be assessed and the efficiency of the parameters is improved. Furthermore, possible biases in the experimental model can be determined and corrected.

(iii) The third objective is to ***validate the jointly estimated models*** by applying the models to alternative data sources. Validation is accomplished by assessing the accuracy of the predictions of the updated models. Alternatively, a sample of data from the original source that was not used for the estimation of the models can be used for validation.

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 the most important variables that should be accounted for are: the pavement structure (materials and strength), traffic (axle configuration and axle loads), environment conditions (temperature and moisture) and any other factors that are relevant for cost allocation.

1.3 Research contributions

The main contribution of this research is not the development of a deterioration model, but rather the demonstration of the feasibility of using joint estimation and its many advantages, such as: (i) identification and quantification of new variables, (ii) efficient parameter estimates, (iii) bias identification and correction, and (iv) use of a measurement error model to combine apparently incompatible data sources.

The most important characteristics of the updated model to predict pavement deterioration in terms of roughness can be summarized as follows:

(i) The updated model predicts roughness incrementally and thus is ideally suited for use within a pavement management context.

(ii) The estimated exponent of the power law indicates that currently used values overestimate the equivalent traffic of the higher load classes, but underestimate the equivalent traffic of the lower load classes.

(iii) The specification allows the determination of equivalent axle loads for different configurations. These estimates revealed that the practice of using the same equivalent load for different axle configurations leads to gross estimation errors of equivalent traffic.

(iv) The specification of pavement strength in terms of the equivalent thickness allows for the determination of the relative contribution of the various materials to the overall pavement strength, even when these material have been used in different experiments.

(v) 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.

(vi) The model indicates that, ceteris paribus, the rate of roughness progression decreases with traffic.

1.4 Dissertation layout

A brief introduction to pavement deterioration was given in the present Chapter together with the goals and objectives of this dissertation.

Chapter 2 contains the literature review. The significance of riding quality as a performance indicator is discussed and some basic definitions are given. Thereafter, some important characteristics of the data sources used for the development of deterioration models are presented and discussed. This discussion is followed by a brief summary of current modeling approaches. The empirical and mechanistic approaches are discussed and their main advantages and disadvantages are highlighted. Chapter 2 concludes with a discussion of current deterioration models.

The main characteristics of the experimental data source, - the AASHO Road Test - are discussed in Chapter 3. Once the data source is described, the basic specification of the proposed deterioration models is given. This is followed by a detailed description of the various components of the model. The Chapter concludes with the formulation of the final specification form for the deterioration model in terms of serviceability (hereafter referred to as the serviceability model).

Chapter 4 deals with the estimation of the serviceability model. The Chapter begins with a discussion of basic concepts of linear and nonlinear estimation. This is followed by a discussion on the use of ordinary least squares (OLS) and random effects (RE) estimation to deal with panel data sets. This chapter concludes with the discussion of three serviceability models. The first model corresponds to the basic specification developed in Chapter 3. The second model is an extension of the basic serviceability model to take into account the performance of the section before and after rehabilitation. The third model extends the basic serviceability model to represent the change of the equivalent thickness of the various pavement layers with time and traffic.

The basic principles of joint estimation are presented in Chapter 5. Some of the main advantages of the technique are discussed. Thereafter, the second data source, -Minnesota Road Research Project (MnRoad)-, is discussed and its main characteristics are presented. This is followed by a discussion on the use of a measurement error model to take into account that the observations of riding quality in the two data sources are recorded in terms of serviceability (AASHO) and roughness (MnRoad). Finally the joint model (in terms of roughness) is given, the parameters of the new model are estimated and the results are discussed.

Chapter 6 presents the conclusions of the dissertation and some recommendations. Finally, some ideas are presented with respect to the future directions of this line of research.

Chapter 2: Literature Review

This Chapter begins with a discussion of the significance of riding quality as a performance indicator, before presenting basic definitions of riding quality and roughness in Section 2.2. A summary of riding quality measurement devices is presented in Section 2.3. This is followed by a discussion of the data characteristics that need to be considered for developing deterioration models. The empirical and the mechanistic approaches to model development are briefly discussed, and their respective advantages and disadvantages are highlighted. Finally, the Chapter concludes with a summary of existing deterioration models and their main characteristics.

2.1 Significance of riding quality

An acceptable riding quality is important for both the road user and the goods being transported. Riding quality affects the comfort of the user for whom the road is provided, and the smoothness with which goods are moved from one point to another. If the riding quality is inadequate, goods could deteriorate in transit resulting in partial or total loss of their economic value. It is thus of economic importance that a paved road will provide adequate riding quality conditions. For this reason pavements are designed to ensure a minimum level of service over their design life. This minimum level of service can be maintained by following different maintenance and rehabilitation (M&R) strategies. The selection of a M&R strategy is based on life-cycle cost analysis of various alternatives.

From the Pavement Engineering point of view, riding quality is a function of the interaction between the longitudinal profile of the pavement and the dynamic characteristics of the vehicles that use that pavement. Hence, vehicles affect pavement deterioration and deterioration affects vehicles, road users and goods in transit.

Riding quality also has other economic implications that are as important as the users' riding quality considerations. Vehicle operating costs and the costs of transporting goods increase as the road riding quality deteriorates. These costs are often one order of magnitude more important than the cost of maintaining the road to an acceptable level of service (Paterson, 1987; GEIPOT, 1982). However, while the costs of maintaining the road are usually incurred by the highway agency, the road users collect the benefits of high riding quality. While maintenance costs are usually included in a life-cycle cost analysis to determine the most economic level of service, the incurrence of vehicle operating costs are often ignored. Previous studies have determined that vehicle operating costs (VOC) typically increase by 2 to 4 percent for each one m/km of IRI in roughness over the range of good to poor conditions (Paterson, 1987). The range for typical paved road pavements is between 2 and 10 m/km IRI.

Despite its economic importance, riding quality is not the most commonly modeled performance indicator for flexible pavements. The most common pavement deterioration models use surface rutting and fatigue cracking as performance indicators, and, to a lesser extent skid resistance.

Rutting is very important because of its safety implications. Rutting in the wheel paths allows water to pond on the surface of the pavement. A vehicle entering this area at normal highway speed may loose contact between the tire and the pavement surface, experiencing hydroplaning. This, in turn, may result in the loss of steering control of the vehicle and result in an accident. Rutting is caused by shear and densification of the pavement layer materials and subgrade.

Cracking, on the other hand, is important from a structural point of view. When cracking of the impervious surface occurs, water may enter the lower untreated layers of the pavement, weakening them. This results in loss of support of the surface layer, which accelerates the deterioration process. Cracking will progress rapidly, causing rutting and potholes to develop. The occurrence of cracking (crack initiation) is a structural problem that, in general, does not affect riding quality. However, it may trigger the acceleration of the deterioration process, as indicated above.

The skid resistance performance of the road is important because of the safety implications. To ensure safe driving conditions, the skid resistance of the pavement surface should be maintained above a minimum threshold.

Riding quality, on the other hand, allows for the economic quantification of the pavement deterioration process. Previous studies (Paterson, 1987; GEIPOT, 1982) have shown that riding quality is the most relevant road performance indicator to be considered when road performance standards are evaluated from an economic point of view. To establish a relevant measure for riding quality, three main elements should be taken into account: (i) the surface profile of the pavement (unevenness), (ii) the dynamic characteristics of the vehicles carrying passengers or goods, and (iii) the road user.

2.2 Basic definitions

In the literature, the terms ***riding quality*** and ***roughness*** are sometimes used as opposites. Strictly speaking from the Pavement Engineering point of view, the term roughness is linked to the quality of the road surface profile. It describes the unevenness of the road surface without considering vehicle interaction or users' perceptions.

According to the American Society for Testing and Materials (ASTM, specification E867-82A), roughness can be defined as: *"the deviations of the surface from a true planar surface with characteristic dimensions that affect vehicle dynamics, ride quality, dynamic loads and drainage"*. After the development of the International Roughness Index (IRI) (Gillespie et al, 1980; Sayers et al, 1986) the term roughness has also been used to refer to the measure of the riding quality in terms of IRI. Subsequently, almost any measure of riding quality or IRI roughness is generally referred to as roughness. In this dissertation, riding quality will, however refer to any measure of the road conditions as perceived by the user, while roughness will be reserved for the cases when that measure is expressed in terms of IRI. The term serviceability will refer to the measure of riding quality in terms of PSI. Finally, the term unevenness will refer to the quality of the surface profile.

2.3 Equipment for measuring riding quality

Riding quality measuring devices can be classified as ***profile-measuring*** or ***response-measuring*** devices. Table 2.1 provides a summary of the most commonly available devices for measuring riding quality.

Profile measuring devices can be classified into three groups: (i) instruments that measure the elevation profile relative to a true horizontal datum, (ii) instruments that measure the road profile relative to a moving datum, and (iii) dynamic profile instruments or profilometers. These devices measure the unevenness of the surface.

Response-measuring devices measure the response of the vehicle to the unevenness of the pavement. These devices can be classified into two groups: (i) devices that measure relative displacement between axle and body of the vehicle, and (ii) devices that measure accelerations of vehicle axle or body by accelerometers and integrate the signal.

Although response-type devices do not measure the surface profile but the response of the vehicle to the surface unevenness, they have been widely used by highway agencies due to their relatively low cost, simple design and high operating speed. This is possible because there are a number of empirical relationships that correlate unevenness statistics with response-type statistics.

Table 2.1: Methods and equipment for measuring riding quality.

Profile measuring devices	Absolute profile	Rod and level survey, Face Dipstick, TRRL Profilometer.
	Moving datum	Profilographs or rolling straight edge devices, CHLOE, Laser Profilometers.
	Dynamic or inertial profilometers	Surface dynamic profilometer: GMR Profilometer, Law Profilometer
		FHWA Profilometer or PRORUT
		APL Profilometer or longitudinal Profile Analyzer
		Low cost profile based devices: South Dakota Profiler, Law Riding quality Surveyor
Response measuring devices	Mechanically based	BPR rough meter, Mays Ride Meter, Bump Integrator, and the NAASRA meter
	Accelerometer based	Automatic Road Analyzer (ARAN), Portable Universal Riding quality Device (PURD), and the Slometer.

Independently of the type of device used, profile-related statistics can be classified into three categories (Sayers et al, 1986). In the first category, the full pavement surface profile is mathematically processed to predict vehicle response.

In the second category, the summary statistic is an estimate of the response of a particular piece of equipment by correlation to a waveform statistic taken from one or more selected wavelengths within the full spectrum. The third category offers more flexibility because the effects across the full spectrum can be evaluated by defining riding quality with respect to different wavelengths. The advantage of using individual wavelengths is that specific effects can be isolated and their effect on pavement performance can be assessed individually. Humans and goods respond more negatively to certain wavelengths and are more immune to others. According to a study by the World Bank (Paterson, 1987): (i) short wavelength unevenness represents defects in the upper pavement layers, (ii) medium wavelength unevenness represents defects deriving from the pavement lower layers, and (iii) long wavelength unevenness represents subsidence or heave deriving from the subgrade.

2.4 Characteristics of the data sources

The importance of an adequate data source deserves to be given some consideration. A number of possible data sources have been used over the years to develop pavement deterioration models. Some of these sources are: (i) randomly selected in-service pavement sections, (ii) in-service pavement sections selected following an experimental design, (iii) purposely built pavement test sections subjected to the action of actual highway traffic and the environment, and (iv) purposely built pavement test sections subjected to the accelerated action of traffic (for example the use of the Heavy Vehicle Simulator (HVS)) and environmental conditions (for example rapid aging by the application of UV radiation).

Due to the nature of the pavement deterioration process, data from actual in-service pavement sections subjected to the combined actions of highway traffic and environmental conditions are desirable. All other data sources produce models that are likely to suffer from some kind of biases or restrictions unless special considerations are taken into account during the parameter estimation. Some of these considerations are briefly described in the following paragraphs.

The most common problems encountered in models developed from randomly selected in-service pavement sections are caused by: (i) the presence of multi-collinearity between relevant explanatory variables, (ii) the unobserved events typical of such data sets, and (iii) the problem of endogeneity bias caused by the use of endogenous variables as independent explanatory variables. These are discussed separately below.

The problem of multi-collinearity 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. There are no statistical methods to address the problem of multi-collinearity because it is a problem inherent to the data set. A typical solution consists of obtaining more data from the original source or to combine various data sources (Archilla, 2000; Archilla and Madanat, 2000).

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 are not properly accounted for, the model may suffer from censoring bias (Paterson, 1987; Prozzi and Madanat, 2000).

Another common problem is endogeneity bias. 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 data from in-service pavement sections that have been selected based on an experimental design.

To overcome some of the above-mentioned problems, purposely built pavement sections subjected to the action of actual traffic and the environment are the best possible sources of data. However, time and budget limitations constrain this type of experiment to a very limited number (e.g., LTPP and Mn/Road High Volume facility). Building pavement test sections and subjecting them to the accelerated action of traffic and the environment solves some of the budget and time constrains (e.g. HVS, Westrack, NCAT, MnRoad Low Volume facility). Accelerated Pavement Testing (APT) facilities also may have mechanical limitations such as the maximum speed of the testing carriage. Thus, this produces models that may be conditional on the testing conditions.

One way of overcoming some of these limitations is through the use of data from multiple sources. Archilla and Madanat (2001) have successfully developed models to predict pavement rutting by combining two different data sources. Both data sources used in his dissertation correspond to experimental test sections. Thus, the 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

2.5 Modeling approaches

Pavement performance models can be categorized into two main groups: empirical models and mechanistic models, depending on the approach followed to develop the performance function. A third group comprises the so-called mechanistic-empirical models that use both mechanistic concepts and empirical methods. Some of the main characteristics of each type are described in the following paragraphs.

Empirical models. In empirical models, the dependent variable is any pavement performance indicator of interest. Both aggregate indicators of performance (such as the Present Serviceability Index (PSI), the Riding Comfort Index (RCI), or the Pavement Condition Index (PCI)) and individual performance indicators (such as skid resistance, rutting, or cracking) have been used as dependent variables. These dependent variables are related to one or more explanatory variables representing pavement structural strength, traffic loading, and environmental conditions.

In some of these models, explanatory variables are used and discarded solely based on considerations of availability and the statistics of their parameters. Often, relevant variables are discarded due to low statistical significance (usually based on the t-statistic of the corresponding parameter). On the other hand, irrelevant variables are often incorporated into the model based on the same considerations. Any model developed following such an approach will undoubtedly suffer from specification biases.

Furthermore, most of the specifications available in the literature are just linear combinations of the available regressors. The criterion typically used to select the best specification form among several alternatives is to obtain the best possible fit to the data (usually measured by the coefficient of determination, R^2).

In the better empirical models, the specification forms are based on physical laws, or at least, they intend to simulate the actual physical process of deterioration. The specification, even when relatively simple (as compared with the actual physical phenomenon), is not constrained to linear equations. Furthermore, relevant regressors, whose parameters are not statistically significant for the given sample, remain in the specification independently of their t-statistics.

Mechanistic models. Mechanistic models are based on a physical representation of the pavement deterioration process. However, due to the complexity of the road deterioration process, this approach is, at present, unfeasible. These deterioration models rely on the use of material behavior and pavement response models, which are believed to represent the actual behavior of the pavement structure under the combined actions of traffic and the environment. These behavior and response models are used to estimate strains, stresses and deflections at various locations in the pavement structure. These critical responses are, in turn, used to predict performance in terms of surface deformation (rutting) and crack propagation (fatigue cracking).

Although there have been various attempts, a comprehensive and reliable model that is purely mechanistic is still to be developed. Material behavior and pavement response models presently used are very simplistic and only represent material and structural responses under restricted conditions.

Mechanistic-empirical models. These models use material characterization (usually laboratory testing) and pavement response models (usually linear elastic or finite element type models) to determine pavement response. This constitutes the mechanistic component. The calculated pavement response (critical strain, stress or deflection) is correlated with pavement performance and finally calibrated to an actual pavement structure. Pavement test sections are used for this purpose as well as in-service pavement sections. This part constitutes the empirical component.

The calibration of these types of models to actual pavement performance is usually done by applying a bias correction factor, usually referred to as the ***shift factor*** (Queiroz, 1983; Theyse et al, 1996; Prozzi and de Beer, 1997; Harvey et al, 1997; Timm et al, 2000). To date the determination of this factor is performed by ad-hoc procedures that are not supported by rigorous statistical analyses, or based on correlations with limited data.

Empirical and mechanistic-empirical models are currently the most widely used deterioration models despite their limitations. Empirical models based on regression analysis have been used for many years and constitute some of the most widely used deterioration models. However, over the past 20 years there has been a tendency for road agencies to direct their efforts toward mechanistic-empirical models because of the appeal from an engineering point of view.

The main advantage, which mechanistic-based models claim, is their ability to extrapolate predictions out of the data range and conditions under which they were calibrated, thus, producing deterministic performance predictions. This advantage constitutes, in turn, their main disadvantage since it is impossible to assess the reliability of the predictions when these models are used out of the original data range for which they have been calibrated.

2.6 Existing models

Linear models based on experimental data. The first pavement performance model was developed based on the data provided by the AASHO Road Test, which took place in Illinois (HRB, 1962). 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:

$$g_t = \frac{p_0 - p_t}{p_0 - p_f} = \left(\frac{N_t}{\rho}\right)^{\omega} \qquad (2.1)$$

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.

By substituting $p_t = p_f$, it can be seen that $\rho = N_t$ at failure. 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 Equation (2.1) in a step-wise linear regression approach. Some of the details of the 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):

$$\omega = \omega_0 + \frac{\beta_0 \, (L_1 + L_2)^{\beta_2}}{(a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4)^{\beta_1} \; L_2^{\beta_3}} \tag{2.2}$$

where

L_1	:	axle load,
L_2	:	1 for single axle vehicles, 2 for tandem axle vehicles,
ω_0	:	a minimum value assigned to ω,
β_1-β_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 and the design and load variables was the following (HRB, 1962):

$$\rho = \frac{\beta_0 \ D^{\beta_1} \ L_2^{\beta_3}}{(L_1 + L_2)^{\beta_2}} \tag{2.3}$$

where

D : $a_1 D_1 + a_2 D_2 + a_3 D_3 + a_4$, represents the structural number (SN), and

β_1-β_3 : regression parameters (not necessarily the same as in Equation 2.2).

In addition to being rather ad hoc, the statistical approach used to estimate the model parameters has several flaws. 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 of Equations (2.1) to (2.3). Moreover, Equations (2.2) and (2.3) are mis-specified 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, Equation (2.1) (or a modification of it) has been used as the basis for pavement design for approximately 50 years (AASHTO, 1981, 1993). This is probably because the AASHO Road Test is the most comprehensive and reliable data source available to date. Besides, the pavement test sections were conceived following a proper experimental design, thus overcoming many of the data limitations usually encountered with data from in-service pavement sections.

Linear models based on field data. A study conducted by the Transportation Road Research Laboratory of the U.K. (TRRL) on in-service road pavements in Kenya provided the additional data needed to update the AASHO models to establish the relationship between pavement riding quality, pavement strength and actual highway traffic (Hodges et al, 1975; Parsley and Robinson, 1980). The use of in-service pavements made it possible to improve over the original AASHO models. Some of these improvements are the incorporation of (i) mixed traffic loading, (ii) different pavement structures over different subgrades, and (iii) a variety of pavement ages. Furthermore, instead of using serviceability as a measure of riding quality, actual measurements of roughness in terms of IRI were used. The following model was developed:

$$R_t = R_0 + f(SN) \ \ N_t \tag{2.4}$$

where

R_t	:	roughness at time t,
R_0	:	initial roughness at time t = 0,
$f(SN)$	:	a function of the structural number SN,
SN	:	structural number developed during the AASHO Road Test (denoted by D in Equation 2.3 above), and
N_t	:	cumulative number of equivalent 80 kN (18,000 lbs) single axle loads applied until time t.

Two main shortcomings have been identified with this model. First, the model was based on pavement structures that consisted of cement-treated bases in 80 percent of the sample. Cement-treated bases are not widely used in the United States. Therefore, they are over represented in the sample and the resulting model is biased. Besides, pavement structures tend to be lighter that those typically used in the United States. Secondly, it assumes the same initial roughness value for all pavement types. The initial roughness after construction is influenced by the type of surface. Thus, the specification should take this into consideration. Another important aspect that affects the initial roughness value is the thickness of the surface layer. As the thickness of the asphalt surface layer increases, the initial roughness after construction decreases.

There are many other examples of linear deterioration models based on field data from in-service pavements. However, many of these studies have failed to quantify the effects of pavement strength, traffic loading and pavement age (time) in the same model. This does not come as a surprise since pavements that are expected to withstand higher levels of traffic are designed to higher strength. Furthermore, cumulative traffic loading and pavement age increase almost simultaneously. This results in high correlations between these variables and therefore it is difficult to assess the individual effects simultaneously. Two different issues arise: (i) multi-collinearity resulting from correlation between two or more explanatory variables (e.g. cumulative traffic and pavement age), and (ii) endogeneity originating from the correlation between the dependent variables and what is assumed to be an independent variable (e.g. pavement strength and pavement life).

A study of ten-year time series data by Way and Eisenberg (1980) failed to identify the effect of traffic loading or pavement strength and developed a model that related roughness to time and pavement age only. The study was based on data from 51 pavement sections in the State of Arizona. The following incremental model was developed:

$$\Delta R_t = \beta_1 \, R_t \, \Delta_t - \beta_2 \qquad (2.5)$$

where

ΔRt : change in roughness level at time t,

Δt : time increment, and

β_1, β_2 : regression parameters that depend on environmental variables.

Even though the model fits the data very well, it suffers from important specification biases. Important explanatory variables are omitted from the specification because the sample failed to characterize their significance. Furthermore, the parameters β_1 and β_2 were estimated by grouping the data into categories according to environmental conditions such as rainfall, elevation, freeze-thaw cycles and temperature. This approach, although valid, does not make optimal use of the data and produces parameters that are not efficiently estimated. The research fails to recognize that important variables that affect the deterioration process are not observed. A preferred estimation approach in this case would consist of pooling all the data together and carrying out an estimation approach that takes into account the unobserved heterogeneity between the various pavement sections. Two such approaches are the fixed effects approach and the random effects approach (Greene, 2000).

The models described in this section are generally useful within the environment under which they have been developed but they are inadequate for generalized technical or economic evaluation of the interaction among the various factors that affect riding quality, i.e., structural properties, traffic loading, age and environmental factors.

Agencies often use regression analysis to develop performance prediction models based on data available in their Pavement Management System (PMS) database. One example of such a model was developed in Alberta (Karan, 1983) with data corresponding to 25 years of observation of riding quality, surface distress, and deflections. The model estimated during that study is:

$$RCI_t = \beta_0 + \beta_1 \ln(RCI_0) + \beta_2 \ln(t^2 + 1) + \beta_3\, t + \beta_4\, t \ln(RCI_0) + \beta_5\, \Delta t \qquad (2.6)$$

where

RCI_t : Riding Comfort Index (scale 0 to 10) at any age t,

RCI_0 : initial RCI at t = 0,

t : age in years,

Δt : years between observations, and

β_1-β_5 : regression parameters.

While a number of other variables were also considered, such as traffic, climate zone, and subgrade soil, only pavement age and RCI were found to be statistically significant. A possible reason is that the pavements were primarily designed in the first place for environmental deterioration, with structural sections significantly thicker than required by traffic alone. This model is an example of statistical fitting: the explanatory variables are selected from what is available according to their statistical significance and without taking into consideration the physical causes of the deterioration process. Regressors are added and removed solely based on the value of their t-statistics, resulting in a biased model.

Similarly, the Department of Transportation of the State of Washington has developed a set of regression equations based on their long-term pavement performance database (Kay et al, 1993). The models have the following general form:

$$PCR = 100 - \beta_1 \, t^{\beta_2} \tag{2.7}$$

where

PCR	:	Pavement Condition Rating (scale 0 to 100), and
β_1, β_2	:	regression parameter

Recommended values for the above parameters have been estimated for Western Washington and are dependent on the type of construction and the surface type. This is a very simplistic specification. Therefore, it has very limited applicability outside the data set from which it was developed. In this case, only one variable was found to be statistical significant so the models suffer from serious specification biases. The parameters are estimated by grouping the data thus resulting in loss of efficiency.

Linear models based on field data and mechanistic principles. The models developed by Queiroz (1983) represent an example of mechanistic-empirical deterioration models. In his work, 63 flexible pavement sections were modeled by means of the multi-layer liner-elastic theory. The calculated responses used in the development of the models were surface deflection, horizontal tensile stress, strain and strain energy at the bottom of the surface asphalt layer, and vertical compressive strain at the top of the subgrade material. Various models were developed to relate the simulated responses to the observed pavement conditions in terms of roughness. Regression analysis was then used to determine the predictive equations. The specified equation for the prediction of roughness is the following:

$$\log(QI_t) = \beta_0 + \beta_1\, t + \beta_2\, ST + \beta_3\, D_1 + \beta_4\, SEN \log N_t \tag{2.8}$$

where

QI_t	:	roughness at time t as measured by the quarter car index in counts/km,
t	:	pavement age in years,
ST	:	dummy variable (0 for original surface and 1 for overlaid surfaces),
D_1	:	thickness of the asphalt layer,
SEN	:	strain energy at the bottom of the asphalt,
N_t	:	cumulative equivalent single axle loads up to time t, and
β_0-β_4	:	regression parameters.

This study represents one of the first attempts to incorporate mechanistic principles into the pavement performance analysis. The strain energy at the bottom of the asphalt is calculated by applying a model based on multi-layer liner-elastic theory. However, the study fails to recognize the uncertainty that is introduced into the procedure by using a multi-layer linear-elastic model to calculate pavement response. This uncertainty is not incorporated into the final model so the model produces deterministic estimations.

Nonlinear models based on field data. A comprehensive study by the World Bank (Paterson, 1987) addressed many shortcomings of previous models by developing a number of empirical models that differ in their level of complexity, accuracy and applicability. The main advantage of these models is the effort that was made to develop a specification that is based on the real physical phenomenon of roughness progression. Moreover, the models were not constrained to be linear and sound statistical techniques were used to estimate the parameters.

The models were based on field data from the Brazil-UNDP Road Cost Study (GEIPOT, 1982; Paterson, 1987), which incorporates a very comprehensive set of cross-sectional data on riding quality, cracking, raveling, rutting, maintenance, traffic and rainfall. Pavement types and strengths, and traffic volumes were selected according to a factorially-designed experiment. By designing the experiment, the sample was selected to minimize the collinearity between time and traffic. The sample comprised heavier pavements subjected to low and high traffic volumes, as well as light pavement structures subjected to high and low traffic volumes.

One of the estimated deterioration models predicts roughness increments by accounting for the interaction of various forms of distress, maintenance activities, pavement strength, traffic loading, age and environmental factors. The basic principle behind this model was that the various parameters and mechanisms that were responsible for roughness progression could be grouped into three categories or components. This categorization was done in terms of the depth of the roughness source within the pavement structure that, in turn, relates to a specific wavelength band.

The first component relates to the surface unevenness resulting from the plastic deformation of the pavement layers under the shear stresses applied by the traffic loading. This is generally associated with distresses occurring in the lower pavement layers. This component accounts for the effects of pavement strength, traffic loading, rutting, and also those environmental effects that relate to the shear strength of the pavement materials.

The second component includes the superficial defects such as cracking, patching, potholes, raveling, etc. This group comprises all localized surface defects that can be associated with shallow distresses originating in the upper pavement layers.

Finally, the third component comprises those environmental conditions that affect the rate of roughness progression, but that do not involve structural damage. These include temperature and moisture effects.

The model was estimated using nonlinear least square regression. The factors that were found to have statistically significant effects on roughness progression included: (i) rut depth variation, pavement strength, cracking, and traffic loading in the structural deformation component; (ii) cracking, patching and potholing in the surface defects component; and (iii) roughness and time in the environmental component of the model. The specified model was the following:

$$\Delta R_t = \beta_1 \, e^{\beta_2 t} \, S^{\beta_3} \, \Delta N + \beta_4 \, \Delta D + \beta_5 \, \Delta C + \beta_6 \, \Delta P + Z + \beta_7 \, R_t \, \Delta t \tag{2.9}$$

where

ΔR_t	:	increase in roughness during time period t,
S	:	a function of *SN*, *H*, and *C*,
SN	:	modified structural number,
H	:	thickness of cracked layer,
C	:	percentage area cracking,
ΔN	:	number of equivalent 80 kN single axles in period t,
ΔD	:	increase in rut depth standard deviation,
ΔC	:	increase in area cracking in period Δt,
ΔP	:	increase in area of surface patching,
Z	:	dummy intercept estimate for sections with potholes,
R_t	:	roughness at time t,
Δt	:	time increment used in the analysis, and
β_1-β_7	:	regression parameters.

The data and the models show that significant deterioration can occur even in the absence of structural weakness. Roughness progression follows a convex trend, with the rate of progression depending initially on the traffic loading relative to the pavement strength and on the environmental conditions.

Paterson (1987) indicated that the model fitted the data well over the wide range of observed roughness increments (up to 7 m/km IRI). This good fit was achieved by introducing many relevant variables. However, the author failed to recognize that a number of variables that were introduced into the model might not be exogenous. This is the case for the structural number that, in general, is a function of the expected traffic. Something similar occurs with the development of cracking and patching. The amount of patching is a function of the amount of cracking. Moreover, cracking progression increases more rapidly as the dynamic load increases due to increased unevenness of the pavement surface. The same applies to the development of rutting and so on.

Despite its limitation, this model is probably one of the best pavement deterioration models available to date. A specification form was developed bearing in mind the deterioration process and not the available data. Only after the model was specified, the parameters were estimated using sound estimation techniques.

2.7 Summary

The literature review revealed that, despite the numerous deterioration models available, most of them are of limited applicability, suffer from important biases, or have been estimated using inadequate methods.

In many instances, even within a given state, pavement performance data is broken down into separate groups and different models are developed for different regions. This approach, although valid, does not make optimal use of the available data. Statistical techniques, such as fixed and random effects are available to address this unobserved heterogeneity.

Also, the vast majority of the models discussed in the literature are inherently linear (linear in the parameters). This constraint is usually placed in the specification form without any apparent reason. The only possible explanation is that the estimation of the parameters of a linear specification can be carried out using a closed form solution. However, currently any desktop computer makes the estimation of nonlinear models a trivial problem.

Another source of specification bias is due to the use of traditional forms, which are often not applicable. For instance, a common assumption in road damage prediction models is the validity of the fourth power law to determine equivalent traffic. Using this approach, traffic loads of different magnitudes and configurations are converted into an equivalent number of 18 kips (80 kN) single axle loads (ESALs). This conversion, although universally accepted and used, has also been extensively criticized over the past 30 years. A number of studies have shown the dependence of this formulation (specifically the value of the exponent of the power law) on the type of distress being considered and the type of pavement structure (CSRA, 1986; Christison, 1986; Prozzi and De Beer, 1997; Archilla and Madanat, 2000). It is known that parameters determined under a given set of conditions are not necessarily valid when those conditions change. A sounder approach would be to determine the exponent during the estimation process whenever the prevailing conditions are different from those predominant during the original AASHO Road Test. Some of the most important conditions to bear in mind are, inter alias, traffic loading configuration, material types, environmental conditions, and failure criteria.

Many of the available specifications have been developed without any serious attempt to represent the physical deterioration process. Although the pavement deterioration process is very complex, the specification should at least attempt to simulate the physical process.

This dissertation presents a methodology aimed at addressing some of the above-mentioned problems and limitations.

Chapter 3: Specification of the Serviceability Models Based on the AASHO Road Test Data Set

This Chapter describes the main characteristics of the basic pavement deterioration model that was developed using data originating from only one data source. The deterioration model is specified in terms of serviceability loss to correspond with the AASHO Road Test data set. The main characteristics of the AASHO Road Test are discussed in Section 3.1. In Section 3.2, the basic model specification is presented. Sections 3.3 to 3.6 describe specific details of the specification form, and in Section 3.7, the final specification of the serviceability model is given.

3.1 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, Illinois (HRB, 1962a and 1962b). The data from this experiment constitutes the most comprehensive and reliable data set available to date. Unfortunately, some of the original raw data have been destroyed, and only summary data tables containing average values are available.

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 annual precipitation in the region of the test was 34 inches (864 mm). This precipitation occurred throughout the year without a significant difference between the dry and wet season. The average temperature during the summer months was 76 °F (24 °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. The rate of frost penetration with time (hereafter referred to as the frost penetration gradient) had an important impact on the performance of the various pavement sections.

Only one subgrade material and one climatic region were evaluated during the AASHO experiment. The upper part of the embankment was constructed with a selected silty-clay material with a CBR value between 2 and 4. These values are representative of large areas in the continental United States. However, although both (climate and subgrade) conditions are typical of large areas in the United States, the use of the results outside these conditions should be subjected to detailed assessment to ascertain their applicability. Estimation of the effects of different subgrade material and environmental conditions cannot be attained with this data set. For this purpose, new data have to be obtained.

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 during the research presented in this dissertation.

Only 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. Table 3.1 shows a summary of the traffic-loading configurations applied to each loop and lane.

Table 3.1: Axle configuration and axle loads during the AASHO Road Test.

Loop	**Lane**	**Axle configuration***	**Weight in kN**		
			Front axle	**Load axle**	**Gross weight**
2	1	1-1	9	9	18
	2	1-1	9	27	36
3	1	1-1-1	18	54	125
	2	1-2-2	27	107	240
4	1	1-1-1	27	80	187
	2	1-2-2	40	142	325
5	1	1-1-1	27	100	227
	2	1-2-2	40	178	396
6	1	1-1-1	40	133	307
	2	1-2-2	53	214	480

* Note: 1-1-1 indicates single front axle and two single rear axles, while 1-2-2 indicates single front axle and two tandem rear axles.

Whenever possible, the traffic moved at 35 mph (56 km/h) on the test tangents. A total of approximately 1,114,000 axle load repetitions were applied from November 1958 until

December 1960. During the experiment, the time was counted by index periods. At the end of each index period readings were taken and recorded. Each index period corresponds to a two-week period; index period 1 started on November 3, 1958.

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 length of the test sections corresponding to the main experimental design (Design 1) was approximately 100 feet (30 meters). In addition to the main experimental design, a number of other tests were performed, increasing the total number of flexible pavement sections to 468.

Most of the sections on the flexible pavement tangents were part of a complete experimental design (Design 1). The design factors considered were surface thickness, base thickness, and subbase thickness. The dimensions of the main factorial designs were 3 x 3 x 3. In other words, 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, varied from 1 to 6 inches (25 to 150 mm), in intervals of one inch (25 mm). The base layer varied in thickness from 0 (no base layer) to 9 inches (0 to 225 mm), in increments of three inches

(75 mm). The thickness of the subbase layer varied from 0 (no subbase layer) to 16 inches (0 to 400 mm), in increments of four inches (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.

The asphalt concrete surface layer consisted of a dense-graded mix with 5.4 percent 85-100 PEN binder content. The coarse aggregate consisted of crushed dolomitic limestone whose maximum size was ¾' (19 mm), and the fine aggregate consisted of natural sand. The maximum size of the crushed stone of the binder coarse was one inch (25 mm), and the AC content was 4.5 percent. The base material was crushed dolomitic limestone with 100 percent passing 1 ½' (38 mm).

The riding quality of the various sections was monitored in terms of their serviceability by means of the Present Serviceability Index (PSI). The PSI varies on a continuous scale from 5.0 PSI for sections in excellent condition to 0.0 PSI for sections in very poor condition. However, for all practical purposes the value for the serviceability rarely exceeds 4.5 PSI and hardly ever falls below 1.5 PSI. It is important to note that the value of the PSI is mainly determined by the slope variance of the test section.

3.2 Basic specification

In addressing the first objective of this research, the data corresponding to the AASHO Road Test was selected for the development and estimation of the experimental pavement deterioration model. The deterioration is evaluated in terms of its loss of riding quality.

This experimental data set was chosen because load and structural variables were selected following an experimental design - thus avoiding many of the data problems described in Chapter 2. 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 (represented graphically in Figure 3.1) was adopted for predicting the loss of serviceability:

$$y = f(z) = a + b\, z^{c} \tag{3.1}$$

where

y : dependent variable representing pavement serviceability,

z : independent variable representing some measure of 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 Equation (3.1), depends on the construction technology and the final thickness of the asphalt surface.

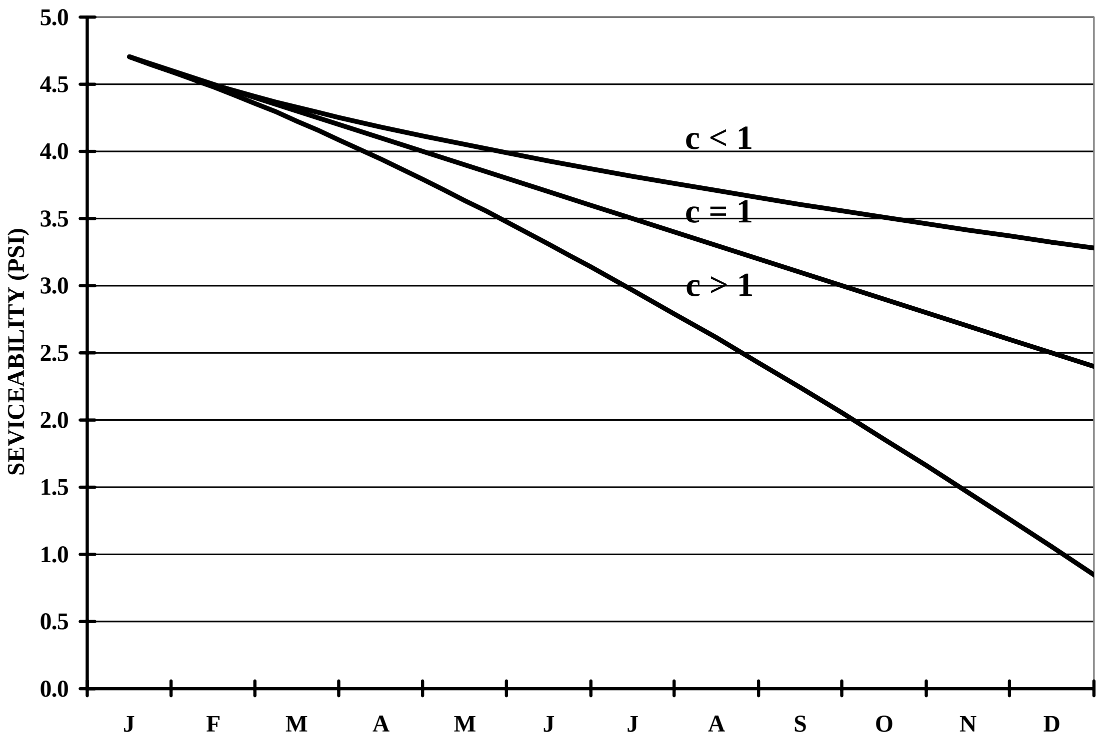

Figure 3.1: Basic proposed shape of the deterioration model based on serviceability.

The selection of the form of the specification was based on the consideration that 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 Equation (3.1) is suitable for predicting pavement serviceability at any time in the life of the pavement, therefore, suitable for design and life cycle analyses. However, from a pavement management perspective, an incremental form is more beneficial since, condition data are usually available on a regular basis and predictions are only desired for the next one or two time periods (typically one or two years).

By using a first order Taylor series approximation, the same specification given in Equation (3.1) can also be used in its incremental form:

$$y_t = y_{t-1} + f'(z_{t-1})\,(z_t - z_{t-1}) \tag{3.2}$$

Thus, the specification form for the incremental model in terms of serviceability and some measure of cumulative traffic becomes:

$$p_t = p_{t-1} + d\ N_{t-1}^{e}\ \Delta N_t \tag{3.3}$$

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 : parameters or functions to be estimated.

By applying the recursive Equation (3.3) from the beginning of the life of the pavement, the following expression is obtained:

$$p_t = p_0 + \sum_{l=1}^{t} d \; N_{l-1}^{e} \; \Delta N_l \tag{3.4}$$

where

p_0 : initial serviceability in PSI at time t = 0.

3.3 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) (AASHO, 1981). The most commonly used form for the determination of the LEF is the so-called ***power law***:

$$LEF = \left(\frac{L}{18}\right)^{\eta} \tag{3.5}$$

where

LEF : load equivalence factor,

L : axle load in kips (1,000 lbs), and

η : parameter that is usually assumed to be between 4.0 and 4.2.

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 (AASHTO, 1981). 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 power law 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 Equation (3.5), converts dual wheeled single axles of different loads into their equivalent number of standard axles. A standard axle was defined as a dual wheel single axle of 18,000 lb (80 kN). Unfortunately, the expression is often used to estimate ESALs for axle configurations other than dual-wheeled single axles.

Bearing these considerations in mind, it was decided, in the present research, to define different power-laws for the different axle configurations present in the experimental data set. Under this assumption, different standard loads (denominator of the power-law) are necessary to transform different axle configurations into 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:

$$EDF = \left(\frac{FA}{18\,\lambda_1}\right)^{\lambda_2} + m_1\left(\frac{SA}{18}\right)^{\lambda_2} + m_2\left(\frac{TA}{18\,\lambda_3}\right)^{\lambda_2} \tag{3.6}$$

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,
$\lambda_1,\lambda_2,\lambda_3$	:	parameters to be estimated, and
m_1, m_2	:	number of single and tandem rear axles per truck, respectively

Equation (3.6) 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 cover the vast majority of truck traffic configurations in the United States.

The equivalent traffic is obtained by multiplying the equivalent damage factor (EDF) of each truck configuration, given by Equation (3.6), by the actual number of truck passes over a given pavement section during time period t:

$$\Delta N_t = n_t\ EDF \tag{3.7}$$

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:

$$N_t = \sum_{l=0}^{t} \Delta N_l \qquad (3.8)$$

3.4 Specification for structural strength

The function *d* in Equation (3.4) 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, 1962b). The thickness index is given by:

$$D = a_1 D_1 + a_2 D_2 + a_3 D_3 \qquad (3.9)$$

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. Thus, the function d is considered to be dependent on the equivalent thickness (ET) according to the following specification:

$$d = ET^{d_0} = \left(1 + d_1\, H_1 + d_2\, H_2 + d_3\, H_3\right)^{d_0} \tag{3.10}$$

where

H_1, H_2, H_3 : thickness of surface, base and subbase layers, respectively,

d_0-d_3 : set of parameters to be estimated, and

ET : equivalent thickness.

Since the value of the function d decreases as the pavement strength increases, the parameter d_0 is expected to be negative (Figure 3.2).

The parameters d_1, d_2, and d_3 in Equation (3.10) 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, 1962a).

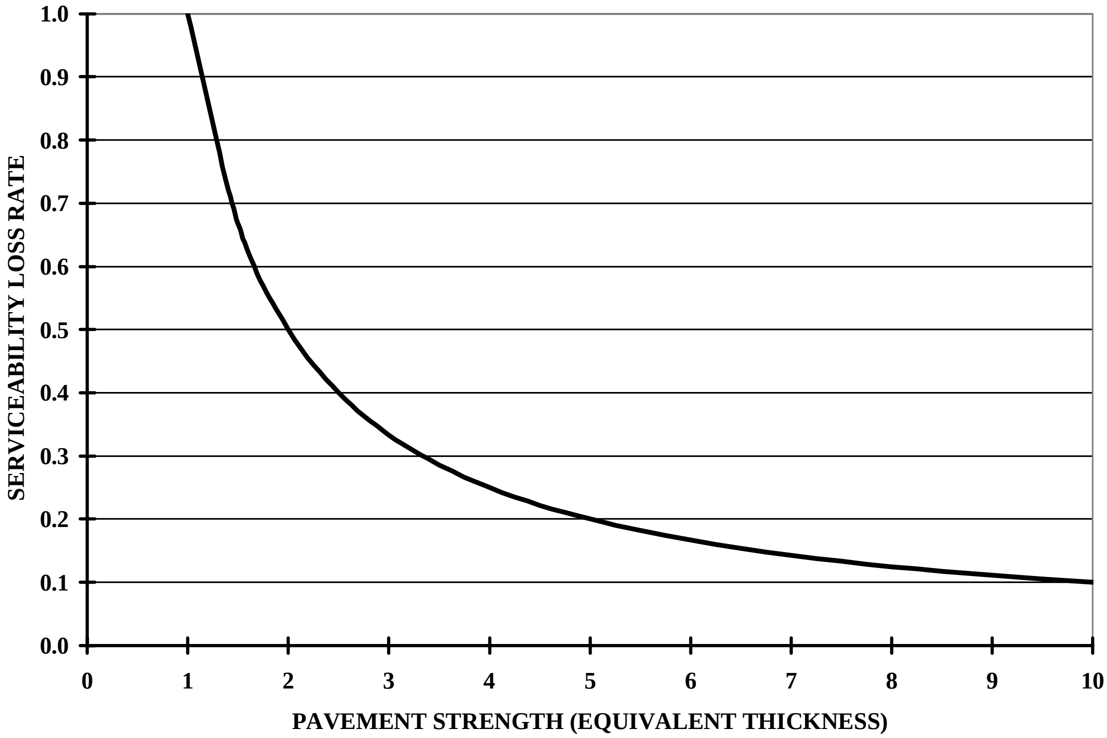

Figure: 3.2: Generic serviceability loss rate as a function of pavement strength.

3.5 Environmental considerations

Environmental conditions are of paramount importance in pavement deterioration. Even in the hypothetical case where the pavement section is not subjected to the action of traffic, deterioration will take place. There are two main considerations that need to be accounted for: (i) the effect of temperature on the stiffness of the asphalt layer, and (ii) the effect of moisture reducing the stiffness of the untreated granular layers.

The viscosity of the asphalt binder decreases as the temperature increases. Thus, the stiffness of the asphalt concrete mixture also varies with temperature. As temperature increases, the stiffness of the asphalt concrete changes by more than one order of magnitude for typical annual temperature variation as that observed during the AASHO Road Test.

At low temperatures the asphalt concrete becomes very stiff and its behavior is similar to that of a Portland cement concrete slab. Furthermore, the change in volume due to the temperature variation and the friction with the lower layers may produce low temperature induced cracking.

The presence of moisture decreases the inter-particle 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.

The effect of environmental conditions can be taken into account following any of two approaches: (i) by taking into account the reduction of the pavement strength, or (ii) by accelerating the effect of the traffic loads. The latter approach was used during the initial analysis of the AASHO Road Test data (HRB, 1962b) by introducing weighting factors. The weighting factors were calculated based on the effect that the environmental conditions had on the surface deflections of the test sections. Where surface deflections were higher than average deflections, the number of truck passes was increased by applying a weight factor larger than one. Conversely, when measured deflections were lower than average values, the number of truck passes was weighted by a factor smaller than one.

In the present study, however, the former approach is followed because it is believed that it represents the actual physical effect of the environment more accurately. An environmental factor is thus 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:

(i) A ***normal phase*** characteristic of the summer and fall periods during which the serviceability decreases at a fairly uniform rate.

(ii) 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.

(iii) 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. Therefore, 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 Figure 3.3.

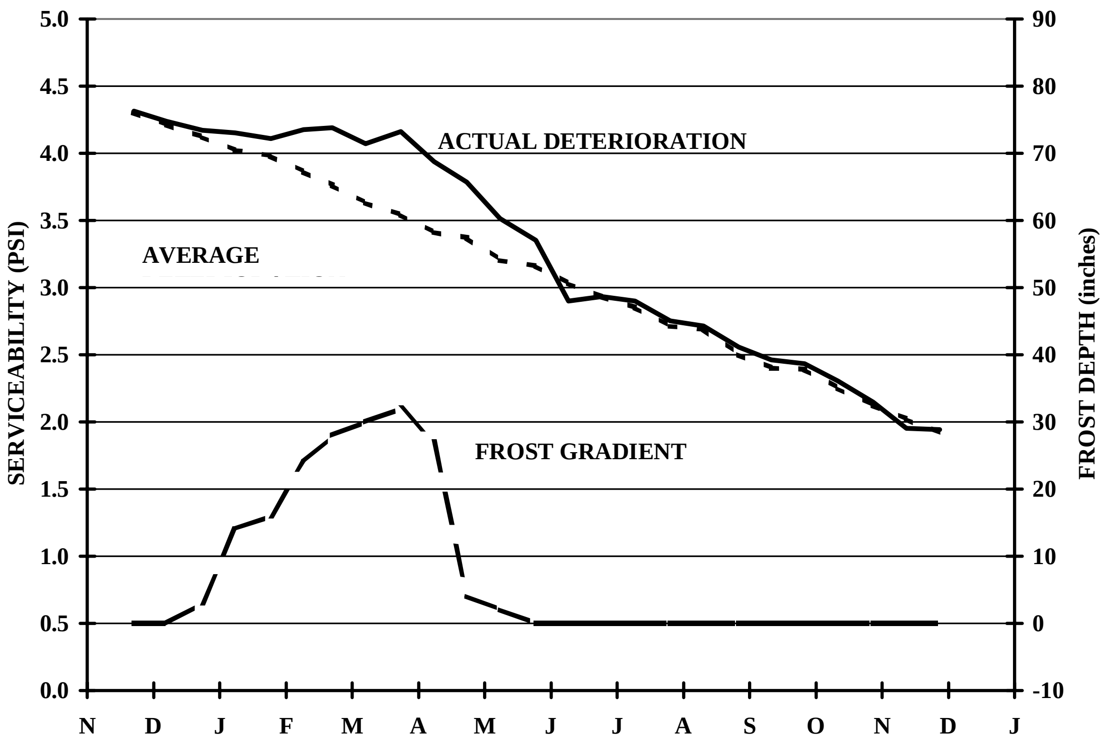

Figure: 3.3: Averaged observed effect of the frost depth on deterioration at AASHO.

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 Equation (3.10). The expression for the environmental factor is as follows:

$$F_e = \exp\{g\ G_t\} \tag{3.11}$$

where

G_t : frost penetration gradient, and

g : parameter to be estimated.

Based on Equation (3.11), three situations are possible:

(i) When the depth of frost penetration is zero ($G_t = 0$), F_e is equal to one so the rate of loss in serviceability is unaffected (normal phase).

(ii) 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).

(iii) 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).

3.6 Specification for initial serviceability

As indicated earlier, the initial value of serviceability of actual in-service flexible pavement sections does not reach the theoretical value of 5.0 PSI for a perfectly planar surface. Furthermore, the initial value (p_0 in Equation (3.4)) 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.

As the thickness of the asphalt surface layer increases, it is usually constructed in various sub-layers 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, it is believed that the initial serviceability could be represented as an increasing function of the asphalt layer thickness. This condition is taken into account in the specification by the following exponential function:

$$p_0 = u + v \exp\{w\, H_1\} \qquad (3.12)$$

where:

u, v, w : parameters to be estimated, and

H_1 : total thickness of the asphalt surface layer.

3.7 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:

$$p_{it} = p_{i0} + \sum_{l=0}^{t-1} d_i \exp\{g\ G_l\} N_{il}^{e} \Delta N_{i,l+1} \qquad (3.13)$$

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 ($i = 1, \ldots, S$), and S is the total number of pavement test sections. The second subscript, t, indicates the time period ($t = 1, \ldots, T_i$). 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 Equation (3.13), the variable d_i is independent of time, and the variable G_l is independent of the section.

For the final formulation all the parameters are renamed as follows:

$$p_{it} = \beta_1 + \beta_2 \exp\{\beta_3 H_{1i}\} + \sum_{l=0}^{t-1} \left(1 + \beta_4 H_{1i} + \beta_5 H_{2i} + \beta_6 H_{3i}\right)^{\beta_7} \exp\{\beta_8 G_l\} N_{il}^{\beta_9} \Delta N_{i,l+1}$$

(3.14a)

Where $N_{il} = \sum_{q=0}^{l} \Delta N_{iq}$, 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 (Table 3.1), the final expression for ΔN_{iq} is the following:

$$\Delta N_{iq} = n_{iq} \left(\left(\frac{FA_i}{\beta_{10} 18} \right)^{\beta_{12}} + m_{1i} \left(\frac{SA_i}{18} \right)^{\beta_{12}} + m_{2i} \left(\frac{TA_i}{\beta_{11} 18} \right)^{\beta_{12}} \right) \tag{3.14b}$$

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

β_1-β_{12} : set of parameters to be estimated using a non-linear optimization method.

Chapter 4: Parameter Estimation of the Serviceability Model

This chapter presents the estimation of the parameters of the serviceability models. Basic linear and non-linear estimation concepts are discussed in Sections 4.1 and 4.2, respectively. A discussion on panel data sets is presented in Section 4.3, while two approaches for estimating with panel data are presented in Section 4.4 (ordinary least squares) and Section 4.5 (random effects). A method for the computation of the error components is given in Section 4.6. The estimated results using ordinary least squares and random effects are presented in Section 4.7, and a more detailed discussion is included in Section 4.8. Finally, two alternative deterioration models based on serviceability are also discussed in this chapter. In Section 4.9, a deterioration model to predict serviceability before and after rehabilitation is presented. In Section 4.10, a model for predicting serviceability that takes into account the change of the strength of the various layers with traffic is presented.

4.1 Linear estimation

The following general functional form is commonly used to represent a relationship that is nonlinear (or linear) in the variables but linear in the parameters:

$$\underline{y} = \underline{X}\,\underline{\beta} + \underline{\varepsilon} \tag{4.1}$$

where

$\underline{y}$: vector of dependent or explained variable,

$\underline{X}$: matrix of independent or explanatory variables,

$\underline{\beta}$: vector of parameters, and

$\underline{\varepsilon}$: vector of random error terms.

The function represented in Equation (4.1) is referred to as the population regression equation of the regressand ($\underline{y}$) on the ***regressors*** or covariates ($\underline{X}$). The most common method of estimating the parameters of the model is the least squares method. The least squares approach yields the following closed form solution for the estimator:

$$\underline{b} = \left(\underline{X}'\,\underline{X}\right)^{-1}\,\underline{X}'\,\underline{y} \tag{4.2}$$

Therefore, $\underline{b}$ is the least squares estimator of $\underline{\beta}$ in Equation (4.1). Under the assumptions of the classical multiple linear regression model (Greene, 2000), the least squares estimator $\underline{b}$ is the minimum variance linear unbiased estimator of $\underline{\beta}$. In the linear regression model, the first order conditions for the least squares estimation of the parameters are linear functions of the parameters. Then, if the matrix $\underline{X}$ is non-singular, Equation (4.2) is a closed form solution for the least squares estimates. Under the assumption of normality the least squares estimator represented by Equation (4.2) is also the maximum likelihood estimator (MLE). The assumption of normality refers to the distribution of the error terms in Equation (4.1).

The estimator $\underline{b}$ is normally distributed with mean $\underline{\beta}$ and variance-covariance (VC) matrix given by:

$$VC(\underline{b}) = \sigma^2 \left(\underline{X}' \, \underline{X}\right)^{-1} \tag{4.3}$$

Where σ^2 is the variance of the error term ε. Since σ^2 is not usually known, the standard error of the regression (*Se*) is used as its estimate. The estimate of the variance-covariance matrix then becomes:

$$Est.\,Var\,(\underline{b}) = Se^2 \left(\underline{X}' \, \underline{X}\right)^{-1} \tag{4.4}$$

Maximum likelihood estimators (MLE) are very desirable because of their large-sample or asymptotic properties. Under regularity conditions (Pindyck and Rubinfeld, 1998; Greene, 2000), the maximum likelihood estimator is consistent and asymptotically efficient.

4.2 Nonlinear estimation

The linear model described in the previous section is very flexible, allowing many shapes of the regression to be used. For instance, by applying simple transformations of the explanatory variables, Equation (4.1) could be used to represent forms that are nonlinear in the variables. However, many useful forms are still ruled out. The range of forms can be expanded substantially by considering models that are intrinsically nonlinear, or nonlinear in the parameters. In this sense, the terms linear and nonlinear refer to the procedure used to estimate the parameters of the specification rather than to the specification form per se. Thus, a general form of the nonlinear regression model can be represented as follows:

$$y_i = h(\underline{x_i}, \underline{\beta}) + \varepsilon_i \tag{4.5}$$

Where h is a nonlinear function of $\underline{\beta}$. Logically, this general specification could also be used for the linear case.

If the assumption is made that the ε_i in Equation (4.5) are 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 now given by:

$$Z_{OLS}(\underline{\beta}) = \frac{1}{2}\sum_{i=1}^{n}\varepsilon_i^2 = \frac{1}{2}\sum_{i=1}^{n}\left[y_i - h(\underline{x_i}, \underline{\beta})\right]^2 \tag{4.6}$$

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 Equation (4.6) are referred to as the least squares estimates of $\underline{\beta}$ or the MLE estimates of $\underline{\beta}$.

Most of the results that are presented in this research for the nonlinear regression models are based on the first-order linear Taylor approximation to $h(\underline{x}\,,\,\underline{\beta})$ at a value of the parameter vector $\underline{\beta}$, which is usually the least squares estimate. The resulting linearized regression model is (Pindyck and Rubinfeld, 1998):

$$h(\underline{x},\underline{\beta}) \approx \left[h(\underline{x},\underline{b}) - \sum_{k=1}^{K} b_k \left(\frac{\partial h(\underline{x},\underline{b})}{\partial b_k} \right) \right] + \sum_{k=1}^{K} \beta_k \left(\frac{\partial h(\underline{x},\underline{b})}{\partial b_k} \right) \tag{4.7}$$

Where K is the total number of parameters to be estimated. For analogy with the linear model the value of the derivatives at the least squares estimates is usually referred to as the ***pseudo-regressors*** (as opposed to regressors as in the linear case). As in the case of the linear model, a consistent estimator of σ^2 is also based on the average of the residuals:

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^{n} \left[y_i - h(\underline{x}_i, \underline{b}) \right]^2 \tag{4.8}$$

Where n is the total number of observations. The estimator in Equation (4.8) is the least square estimator as well as the maximum likelihood estimator. Therefore, it is consistent and asymptotically efficient. The degrees of freedom correction is not applied because the results are asymptotic.

Assuming that the pseudo-regressors defined in Equation (4.7) are well behaved (Greene, 2000), the sample estimate of the asymptotic variance-covariance matrix can be obtained as follows:

$$Est.\ Asy.Var(b) = \hat{\sigma}^2 \left(\underline{X}^{0}{}' \underline{X}^{0} \right)^{-1} \tag{4.9}$$

Where the matrix $\underline{X}^0$ is evaluated at the least squares estimate of $\underline{\beta}$ as follows:

$$\underline{X}^{0}{}' \underline{X}^{0} = \sum_{i=1}^{n} \left(\frac{\partial h(\underline{x}_i, \underline{\beta})}{\partial \underline{\beta}} \right) \left(\frac{\partial h(\underline{x}_i, \underline{\beta})}{\partial \underline{\beta}'} \right) \tag{4.10}$$

4.3 Panel data

The data set corresponding to the AASHO Road Test data set consists of panel data. In other words, observations of pavement deterioration are available along time (time series data) and for many sections (cross sectional data). Several approaches can be followed to undertake estimation with panel data. The simplest approach estimates one time series regression for each section or, alternatively, one cross- sectional regression at each point in time. These techniques are frequently used in the literature, but depending on the assumptions, there may be more appropriate techniques to be used. For instance, 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 result 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. A typical example of one of these unobserved section-specific variables is the variability of the density of the pavement layers as a result of the construction process. For instance, the aggregate base layer acts as the support platform for the construction of the asphalt surface. Thus, non-uniformity of the density of the base across sections could affect the initial conditions of the different pavement sections in a different way.

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. In Sections 4.5 and 4.6, a method to deal with the unobserved heterogeneity using the so-called random effects model, is presented. This method assumes that the unobserved heterogeneity can be captured by an intercept term, which is assumed to be normally distributed in the population.

4.4 Ordinary least squares (OLS)

Equation (3.14), presented at the end of Chapter 3, represents the conditional expectation of the riding quality (expressed in terms of serviceability) at a given time t for a given section i. This expectation is conditional on a vector of parameters $\underline{\beta} = \beta_1, \ldots, \beta_{12}$ and a set of explanatory variables ($\underline{X}_{it}$) which take on a specific value ($\underline{x}_{it}$) for a given section i and at a given time t. These variables describe the combination of pavement properties (H_{1i}, H_{2i}, H_{3i}), traffic characteristics (FA_i, SA_i, TA_i) and environmental conditions (G_t) at a given time for a given section.

By applying the specification to all observations (all sections $i = 1, \ldots, S$, and all time periods $t = 1, \ldots, T_i$) the following set of equations results:

$$p_{it} = E\left(p_{it} \mid \underline{x}_{it}, \underline{\beta}\right) + \varepsilon_{it} \tag{4.11}$$

Equation (4.11) is not linear in the parameters, so the estimation of the parameters does not have a closed form solution. A nonlinear minimization routine has to be used to obtain the parameter estimates. The following two assumptions are necessary to proceed with the estimation:

(i) the random error term ε_{it} is assumed to have mean zero and constant variance: $E(\varepsilon_{it}) = 0$, and σ_ε^2 is constant across sections and along time, and

(ii) the covariance of the error terms is zero across sections and along time:

Cov (ε_{it} , ε_{jr}) = 0, for i $\neq$ j or t $\neq$ r.

Given these two assumptions, the nonlinear ordinary least squares estimate of the parameters is obtained by minimizing the following objective function:

$$Z = \frac{1}{n}\sum_{i=1}^{S}\sum_{t=1}^{Ti}\left(p_{it} - E\left(p_{it} \mid \underline{x_{it}}, \underline{\beta}\right)\right)^2 \tag{4.12}$$

Where S is the total number of test sections, T_i the observations at section i, and $n = \sum_{i=1}^{S} T_i$, is the total number of observations. It should be noted that the number of observations per section (T_i) is not constant, because some sections were removed from the experiment before the end of the test due to failure.

4.5 Unobserved heterogeneity: random effects model (RE)

By using least squares estimation the presence of unobserved heterogeneity is ignored. That is, the assumption is made that all relevant variables that could affect the deterioration of the various sections differently have been observed and are incorporated into the deterioration model. However, it is often the case, especially when dealing with large cross sectional information (large number of sections), that some degree of unobserved heterogeneity is present.

Two basic approaches are commonly used to deal with this problem: fixed and random effects. Both these approaches make the assumption that the unobserved differences across pavement sections can be captured by the intercept term. In the fixed effects approach, one intercept term is estimated for each pavement section. The random effects approach assumes that the intercept term is a section specific disturbance and that there is a single draw per section that enters the regression identically in each period (Greene, 2000). Although the fixed effects approach renders consistent estimates for a large number of pavement sections, it is costly in terms of the degrees of freedom that are lost (especially when the number of sections is large). Besides, the intercept estimates are relevant to the sample used in the estimation process, but do not reveal any relevant characteristics of distribution of the intercept term in the population. 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:

$$y_{it} = \alpha + \underline{\beta}' \underline{x}_{it} + u_i + \varepsilon_{it} \tag{4.13}$$

The following set of assumptions is necessary to formulate and estimate the model using the random effects approach (Greene, 2000):

$$E(\varepsilon_{it}) = E(u_i) = 0$$

$$E(\varepsilon^2_{it}) = \sigma^2_\varepsilon$$

$$E(u^2_i) = \sigma^2_u$$

$$E(\varepsilon_{it} u_j) = 0 \text{, for all } i, t, \text{ and } j \tag{4.14}$$

$$E(\varepsilon_{it} \varepsilon_{js}) = 0 \text{, if } t \neq s \text{ or } i \neq j$$

$$E(u_i u_j) = 0 \text{, if } i \neq j$$

Letting $w_{it} = \varepsilon_{it} + u_i$, then for all observations of section i, the sum of the two error components is given by:

$$\underline{w_i} = [w_{i1}, w_{i2}, \ldots, w_{iTi}]' \tag{4.15}$$

Then, for the given model under the above-mentioned assumptions:

$$E(w^2_{it}) = \sigma^2_\varepsilon + \sigma^2_u \tag{4.15}$$

$$E(w_{it} w_{is}) = \sigma^2_u \quad , t \neq s$$

Letting $\Omega_i = E(\underline{w}_i \underline{w}_i')$ for the T_i observations corresponding to section i, then:

$$\underline{\Omega}_i = \begin{bmatrix} \sigma_\varepsilon^2 + \sigma_u^2 & \sigma_u^2 & \dots & \sigma_u^2 \\ \sigma_u^2 & \sigma_\varepsilon^2 + \sigma_u^2 & \dots & \sigma_u^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_u^2 & \sigma_u^2 & \dots & \sigma_\varepsilon^2 + \sigma_u^2 \end{bmatrix} = \sigma_\varepsilon^2 \; I_{Ti} + \sigma_u^2 \; \underline{i}_{Ti} \underline{i}_{Ti}' \tag{4.17}$$

where

$\underline{i}_{Ti}$: a T_i by 1 column vector of ones, and

$\underline{I}_{Ti}$: identity matrix of dimension T_i.

Since the observations of a given pavement test section are independent from the observations for another test section, the disturbance covariance matrix for all observations along time ($t = 1$ to T_i) and across sections ($i = 1$ to S) is $\underline{V} = \underline{\Omega} \otimes \underline{I}_n$. However, for the generalized least squares only the inverse of the matrix $\underline{V}$ is required for which only the inverse of $\underline{\Omega}$ is needed. The inverse of $\underline{\Omega}$ is given by:

$$\underline{\Omega}_i^{-1} = \frac{1}{\sigma_\varepsilon^2}\left(\underline{I}_T - \frac{\sigma_u^2}{\sigma_\varepsilon^2 + T_i \sigma_u^2} \underline{i}_T \underline{i}'_T \right) = \frac{1}{\sigma_\varepsilon^2} \underline{W}_i \tag{4.18}$$

The generalized least squares (GLS) estimator can be used when the variance of the error components σ^2_ε and σ^2_u are known. In this case, the random effects estimates of $\underline{\beta}$ can be obtained by minimizing the following objective function:

$$Z_{RE} = \sum_{i=1}^{S} \left(\underline{p}_i - E_i(\underline{\beta})\right)' W_i \left(\underline{p}_i - E_i(\underline{\beta})\right) \tag{4.19}$$

where

$\underline{p}_i$: vector of measured serviceability for section i , and

$E_i\ (\underline{\beta})$: vector of predicted serviceability for section *i*.

4.6 Computation of the error components

For the experiment under consideration, the components σ^2_ε and σ^2_u are unknown. Hence, feasible generalized least squares (FGLS) has to be applied to estimate the values of the vector of parameters $\underline{\beta}$. Therefore, estimates of σ^2_ε and σ^2_u are required. The traditional approach is to obtain alternative estimates of $\underline{\beta}$ and then, use these estimates to obtain estimates for σ^2_ε and σ^2_u. It should be noted that, although heterogeneity is expected, the OLS approach still yields consistent estimates of $\underline{\beta}$. With the OLS estimates of the parameters in hand, the following statistics have to be computed (Greene, 2000; Archilla, 2000) for $i = 1$ to S and $t = 1$ to T_i to estimate the error components:

$$e_{it} = p_{it} - E\left(\underline{x}_{it}, \underline{b}\right) \tag{4.20}$$

$$\overline{e_{i.}} = \frac{\sum_{t=1}^{Ti} e_{it}}{Ti} \tag{4.21}$$

$$e_{**i} = \overline{p}_{i.} - \overline{E}_{i.}(x_{it}, b) \tag{4.22}$$

Where $p_{i.}$ and $E_{i.}$ (x_{it}, b) are the average measured and predicted serviceability for section i, respectively. Finally, the estimation of the regression error component (σ^2_ε) is done as follows (Greene, 2000):

$$\hat{\sigma}_\varepsilon^2 = \frac{\sum_{i=1}^{S}\sum_{t=1}^{Ti}\left(e_{it} - \overline{e}_{i.}\right)^2}{\sum_{i=1}^{S} Ti - S - K + 1} \tag{4.23}$$

Where S is the number of pavement test sections and K is the number of estimated parameters corresponding to Equation (4.10). On the other hand, the estimation of the section specific error component (σ^2_u) is obtained as follows:

$$\hat{\sigma}_u^2 = \frac{\underline{e}_{**}^{'}\,\underline{e}_{**}}{S - K + 1} - \hat{\sigma}_\varepsilon^2\, Q_S \tag{4.24}$$

Where $\underline{e}_{**} = [e_{**1}, \ldots, e_{**S}]$, and $Q_S = \frac{1}{S}\sum_{i=1}^{S}\frac{1}{T_i}$.

Once the estimates of σ^2_ε and σ^2_u are computed with Equations (4.23) and (4.24) the feasible generalized least squares estimates of $\underline{\beta}$ can be obtained by minimizing the objective function given in Equation (4.18). Finally, the estimate of the variance-covariance matrix of the random effects estimates of $\underline{\beta}$ is obtained by:

$$Est.\,Var\left(\underline{\beta}\right) = \sum_{i=1}^{S} \underline{X}_i^{0}{}' \, \underline{\hat{\Omega}}_i^{-1} \, \underline{X}_i^{0} \tag{4.25}$$

Where $\underline{X}_i^0$ and $\underline{\Omega}_i$ are defined in the previous sections by Equations (4.10) and (4.17), respectively.

4.7 Comparison of the results of OLS and RE estimation

The parameters of the serviceability deterioration model (Equation (3.13)) 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 4.1. The estimates in Table 4.1 were obtained using only the data originated from the AASHO Road Test. Table 4.1 shows that all the parameter estimates are statistically significantly different from zero at a five percent level and all the parameters have the correct 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 (HRB, 1962b). 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 mainly the result of a better specified model due to the relaxation of the linear constraint.

Table 4.1: Parameter estimates and asymptotic t-values for the OLS and 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

The above discussion highlights the three most important aspects that need to be taken into account when estimating pavement deterioration models: (i) a physically realistic model specification, (ii) an adequate data source, and (iii) statistically sound estimation techniques. A strong theoretical background should support the model specification. The data should be obtained from a well-conceived experimentally designed test aimed at addressing all the important variables that have been identified during the development of the theory. And finally, the correct estimation approach should be utilized.

Table 4.1 also illustrates the difference in the estimates obtained between the ***wrong*** approach (OLS) and the ***correct*** approach (RE). Although the differences in some of the estimated parameters are relatively small, it could be very significant, as is the case of the exponent of the power-law. This aspect is discussed in detail in the next section.

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.

Statistical testing was carried out to objectively verify whether the extent of unobserved heterogeneity could be ignored. For this purpose, a Lagrange multiplier (LM) test was performed to determine whether the estimated $\hat{\sigma}_u^2$ is significantly different from zero (Breusch and Pagan, 1980). The LM was significantly different from zero at a five percent level and, therefore, unobserved heterogeneity could not be ignored in the present sample. Hence, the results of the random effect estimation should be regarded correct.

4.8 Discussion of the serviceability model

Parameters β_1, β_2, and β_3 are used to model the effect of the asphalt thickness on the value of the initial serviceability after construction. This effect is represented graphically in Figure 4.1. As can be seen, the initial serviceability value estimated from this sample varies from 2.91 PSI associated with a hypothetical asphalt thickness $H_1 = 0$ to 4.24 PSI as the asphalt thickness increases towards infinity - thus never reaching the maximum theoretical value of 5.0 PSI. It should be noted that observed surface asphalt thicknesses at the AASHO Road Test varied from 1 to 6 inches. Although hypothetical zero asphalt thicknesses are common in pavements (unpaved roads), the serviceability model presented in this dissertation is not applicable to this situation.

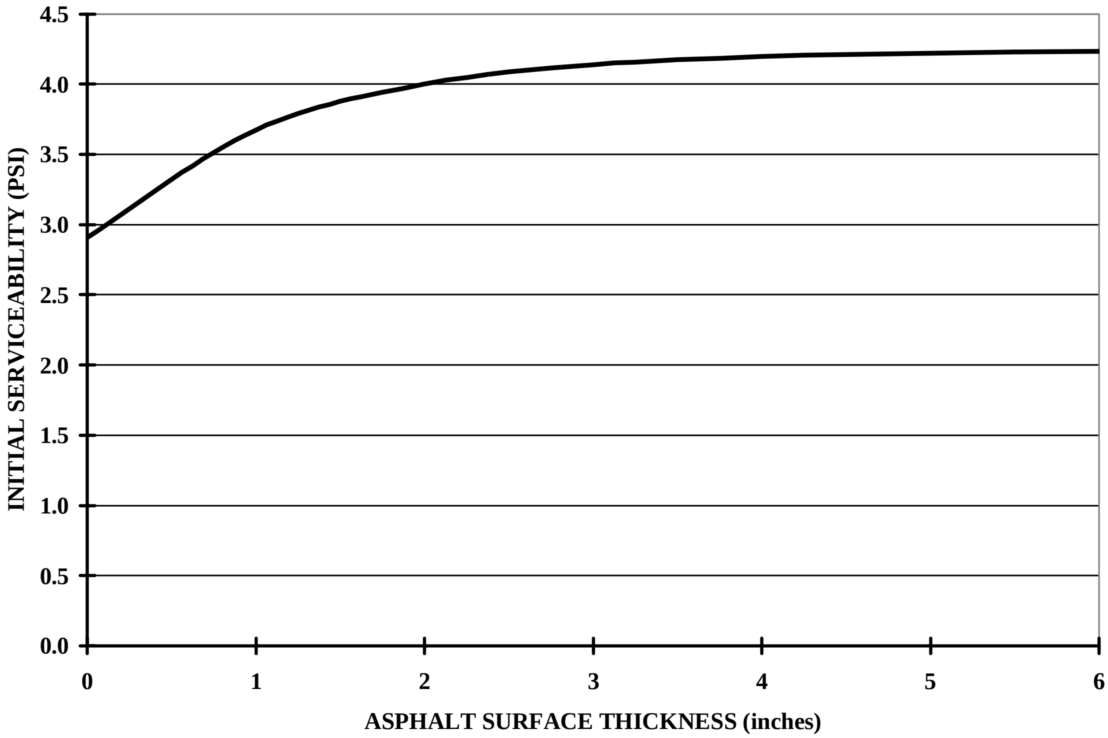

Figure 4.1: Variation of the initial serviceability with asphalt surface thickness.

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, 1962a). 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. These results indicate that one inch of asphalt is as effective as four inches of granular base in protecting the pavement section from deterioration due to loss of serviceability. Accordingly, one inch of granular base layer is 20 percent more effective than one inch of subbase. These estimates enable the selection of the final thickness combination of the various pavement layers on an economic basis. These estimates are only applicable when the relative strength of the surface, base and subbase materials are similar to those present at the AASHO Road Test.

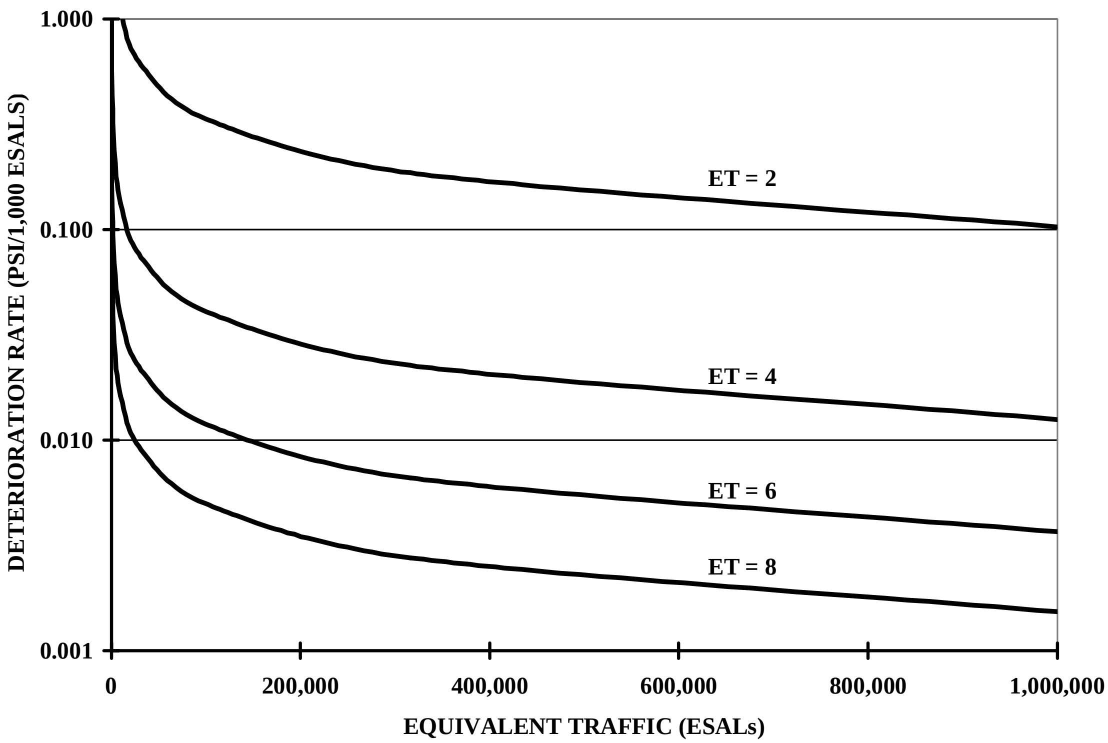

Figure 4.2: Deterioration rate as a function of strength and traffic.

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 Figure 4.2. 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 Figure 4.2, the rate of deterioration decreases with cumulative traffic. This is represented by the parameter β_9 in the specification, whose sign is negative.

It is important to note that the concept of equivalent thickness is applicable within reasonable ranges of surface, base and subbase thicknesses. Besides, the specification was developed for pavement structures in which the material strength decreases with depth. The application of the equivalent thickness concept to inverted pavements (those with strong materials supporting weaker ones) is matter of further research, outside the scope of this dissertation.

The rate of serviceability loss is also affected by the environmental conditions because these conditions affect pavement strength. In the present deterioration model, this is taken into account by the effect of the frost penetration gradient G. Since the sign of the parameter β_8 is negative, it indicates that for a positive gradient (depth of frost penetration increasing with time) the environmental factor F_e is smaller than one. Hence, the rate of serviceability loss is reduced. This effect is shown in Figure 4.3.

It can be seen from Figure 4.3 that as the depth of frost penetration decreases - as a result of the fall thawing period - the frost gradient (G) becomes negative and the environmental factor becomes larger than one. Hence, the rate of serviceability loss increases.

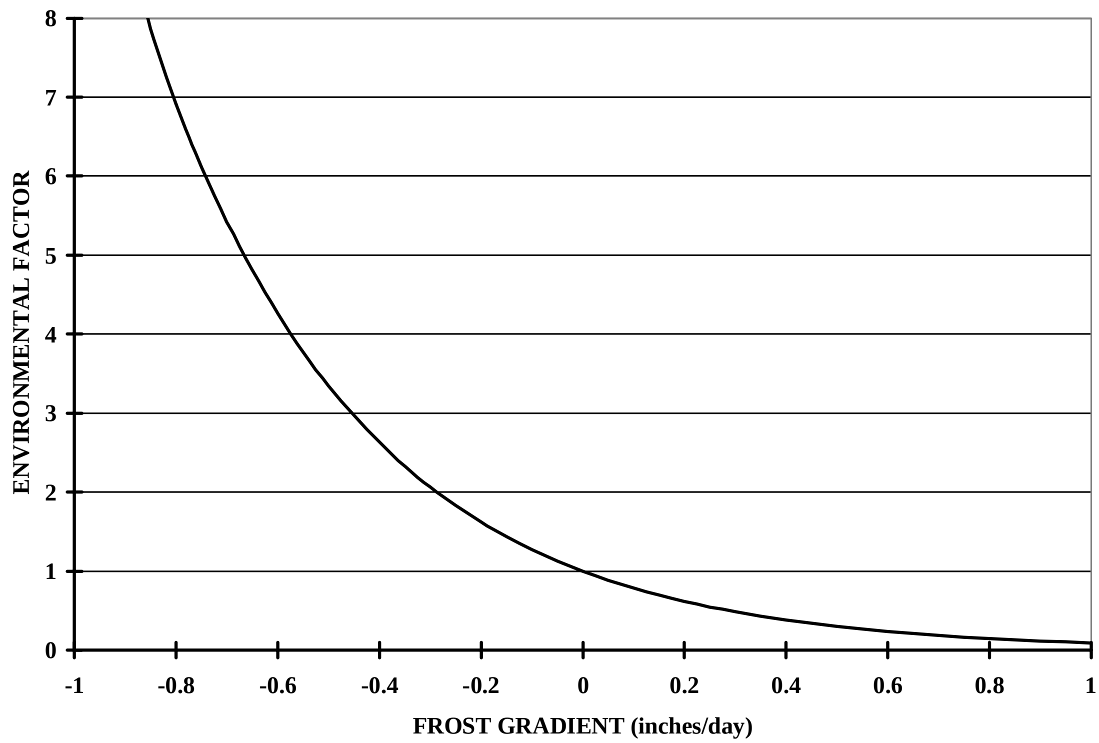

Figure 4.3: Variation of environmental factor (Fe) with the frost gradient (G).

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 estimated EDFs for the different axle configurations considered are represented graphically in Figure 4.4.

The 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 (see Figure 4.4).

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

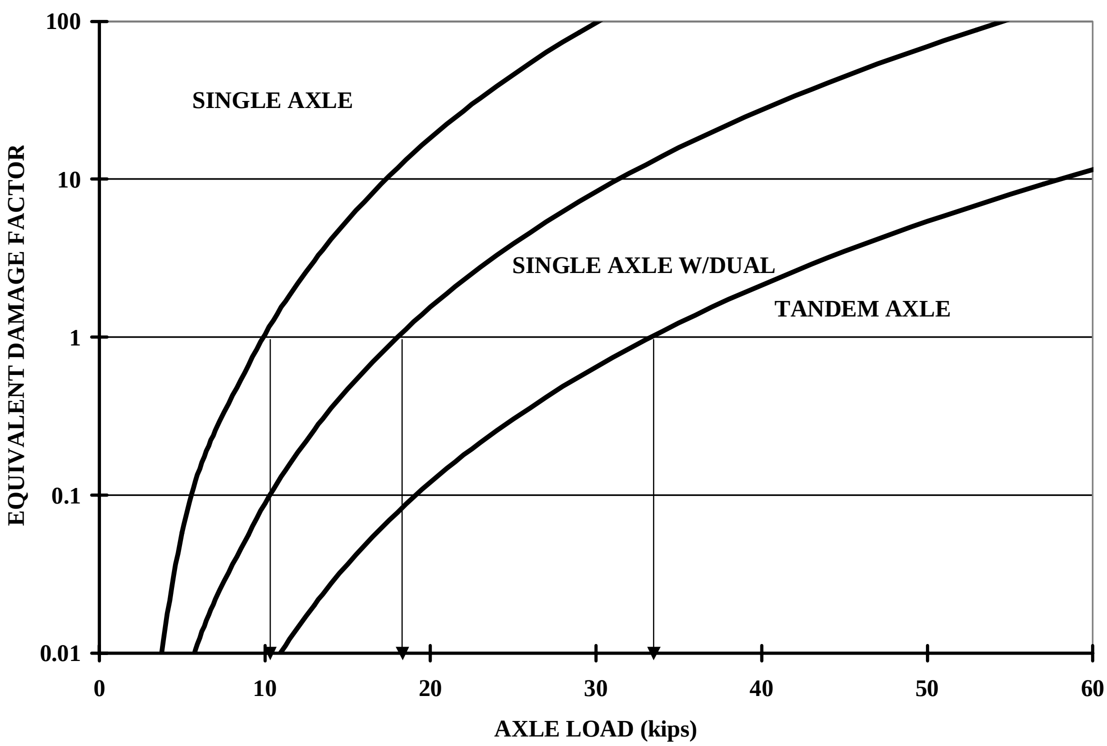

Figure 4.4: Equivalent Damage Factors (EDFs) and equivalent loads.

It should be emphasized that the above estimated equivalent loads were estimated to produce the same damage to the road in terms of serviceability loss. Thus, they should only be applied to determine EDFs when riding quality considerations are used in an analysis. If fatigue cracking, surface rutting, skid resistance or other indicators of performance were utilized, these equivalent loads would not necessarily apply.

The specification of EDF assumes the same exponent of the power law for all axle configurations. This formulation is consistent with the traditional approach, especially, when damage is determined in terms of considerations of riding quality. When other performance indicators are used, different exponents should be considered for the various configurations. This is especially the case for rutting models, as was demonstrated by Archilla (2000).

4.9 Serviceability deterioration model before and after the overlay

At the AASHO Road Test, experimental traffic loading was applied for approximately two years. During this period, a number of test sections failed and were rehabilitated by means of an asphalt overlay. The data thus enables the specification and estimation of pavement deterioration models to estimate the section performance before and after the overlay. Such models are scarce in the literature, but can offer important benefits to the manager of the highway system. By incorporating the effect of the overlay on pavement performance, life cycle cost studies can be carried out objectively. For instance, the model can assess the effect of applying different overlay thicknesses at different points in time on pavement performance.

To account for the asphalt overlay, three modifications to the original deterioration model described in Section 4.7 and 4.8 are incorporated. The first modification takes into account that the asphalt overlay will increase the overall pavement strength. This is taken into account by adding the overlay thickness when determining the equivalent pavement thickness (ET).

The second modification relates to the fact that the deterioration rate decreases with cumulative traffic after construction. Once the pavement section is rehabilitated with an asphalt overlay, the condition of the pavement is ***reset*** to a new initial condition, which is not necessarily the same as the condition of the new pavement. Hence, the rate of deterioration immediately after rehabilitation should also be reset to some initial value.

The final modification accounts for the fact that the initial serviceability value after rehabilitation is not necessarily the same as the value after initial construction. This value is expected to be somewhat lower, because the new working platform for the construction of the overlay is relatively uneven.

As a result of these three modifications, the new specification form is the following:

$$p_{it} = \beta_1(1-O_{ti}) + \beta_{13}O_{ti} + \beta_2 \exp\{\beta_3 H_{1i}(1-O_{ti}) + H_{0i}O_{ti}\} + \ldots \tag{4.26}$$

$$+\sum_{l=0}^{t-1}\left(1+\beta_4(H_{1i}+H_{0i})+\beta_5 H_{2i}+\beta_6 H_{3i}\right)^{\beta_7}\ \exp\{\beta_8 G_l\} N_{il}^{\beta_9}\,\Delta N_{i,l+1}$$

Where all the variables and parameters have the same meaning as before but the variable N_{it} represents the cumulative traffic after the last construction work, i.e., since new construction or rehabilitation. The variable O_{it} is a dummy variable, which takes the value zero when no overlay is present, and takes the value one when an overlay exists in the section *i* at time period *t*. The estimated parameters (using the random effects approach) as well as their asymptotic statistics are given in Table 4.2.

Table 4.2: Estimated parameters for the serviceability model with an overlay.

Parameter	Estimated value	Asymptotic t-value
β_1	4.16	256.9
β_2	-1.65	-2.3
β_3	-1.70	-3.9
β_4	1.49	17.7
β_5	0.312	16.1
β_6	0.180	18.1
β_7	-3.13	-39.3
β_8	-0.165	-45.0
β_9	-0.506	-49.6
β_{10}	0.557	26.6
β_{11}	1.80	106.0
β_{12}	3.90	51.2
β_{13}	3.49	179.0

The estimated variances of the two error components are $\hat{\sigma}_{\varepsilon}^2 = 0.140$ (overall error) and $\hat{\sigma}_u^2 = 0.121$ (section specific error). Thus, the estimated standard error of the regression is approximately 0.51 PSI, which as in the case of the original model described in Section 4.8, is about half of the error of the model derived during the original analyses undertaken by AASHO and The Asphalt Institute (HRB, 1962b; Painter, 1965).

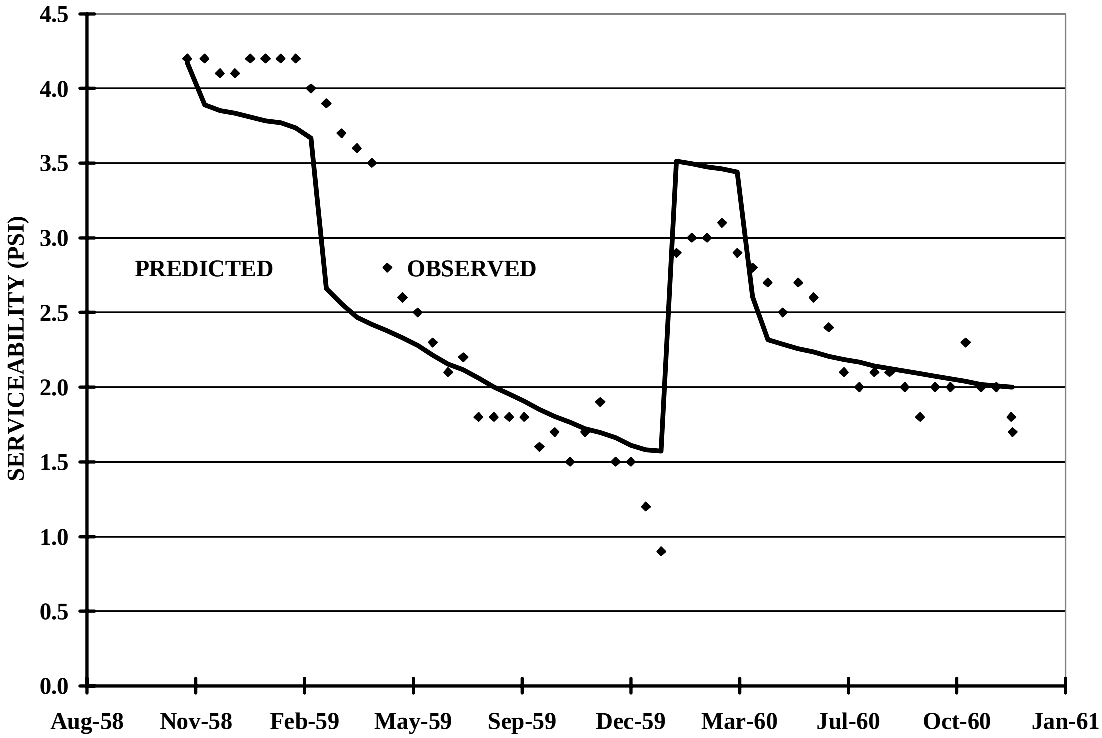

Figure 4.5: Observed and predicted serviceability for a rehabilitated section.

Figure 4.5 presents an example of the observed and predicted serviceability values for a rehabilitated section. As can be seen, the model is relatively good at estimating the deterioration of the section. Especially, it accurately captures the increase in the deterioration rate during the critical fall period, and increase in the serviceability value after the asphalt overlay.

4.10 Variation of layer strength coefficients with traffic

The parameters β_4, β_5, and β_6 are usually referred to as the layer strength coefficients, because their magnitudes are related to the relative strength of the specific layer material (HRB, 1962a; Painter, 1965). As a result of the estimation process, the estimated parameter values represent the relative strength of the various materials ***averaged*** over the pavement life. Therefore, the estimated values do not necessarily bear a direct relationship with the material strength parameter measured in the laboratory. Laboratory testing is performed on the materials under the conditions the materials are expected to be directly after construction. Laboratory conditions (such as density or stiffness) are intended to represent the initial material properties.

The data used to estimate the parameter values given in Table 4.1 (as well as the strength coefficients used for the determination of the thickness index D) correspond to the main factorial design of the AASHO Road Test (Design 1) (HRB, 1962a). Only one asphalt mixture, one base, and one subbase material types were used for the construction of all the test sections. If the performance of pavement sections that were constructed with different materials to the original ones were to be estimated with Equation 3.14, new strength coefficients would, in general, have to be used.

Traditionally, the estimation of strength coefficients for new materials is done by comparing the strength of the new materials with the strength of the original materials. Laboratory and in-situ testing are commonly used for this purpose. However, as indicated earlier, these tests only assess the initial conditions of the materials and no consideration is given to the average condition of the material over the entire pavement life. These considerations lead to an alternative specification for the pavement strength as follows:

$$ET = 1 + \beta_4 e^{\beta_{13} N} H_1 + \beta_5 e^{\beta_{14} N} H_2 + \beta_6 e^{\beta_{15} N} H_3 \tag{4.27}$$

where

ET	:	equivalent pavement thickness as a function of cumulative traffic,
$\beta_{13}, \beta_{14}, \beta_{15}$	:	additional parameters to be estimated, and
N	:	cumulative traffic expressed in ESALs.

In this modified specification the parameters β_4, β_5 and β_6 can be related to the initial material conditions and, therefore, to laboratory testing. On the other hand, the parameters β_{13}, β_{14} and β_{15} take into account the change in material strength with traffic. The estimated variation of the value of the strength parameter with traffic is presented graphically in Figure 4.6.

The new set of estimated parameters and their corresponding asymptotic statistics are given in Table 4.3. The estimated variances of the two error components are $\hat{\sigma}_{\varepsilon}^2 = 0.140$ and $\hat{\sigma}_u^2 = 0.121$, so the standard error of the regression is 0.51 PSI.

The new model predicts that the relative strength of the surface layer would decrease with traffic, probably due to fatigue damage of the asphalt mixture. On the other hand, the relative strength of the base and subbase layers seems to increase as traffic increases. This is probably due to the increase in density as a result of the additional traffic compaction.

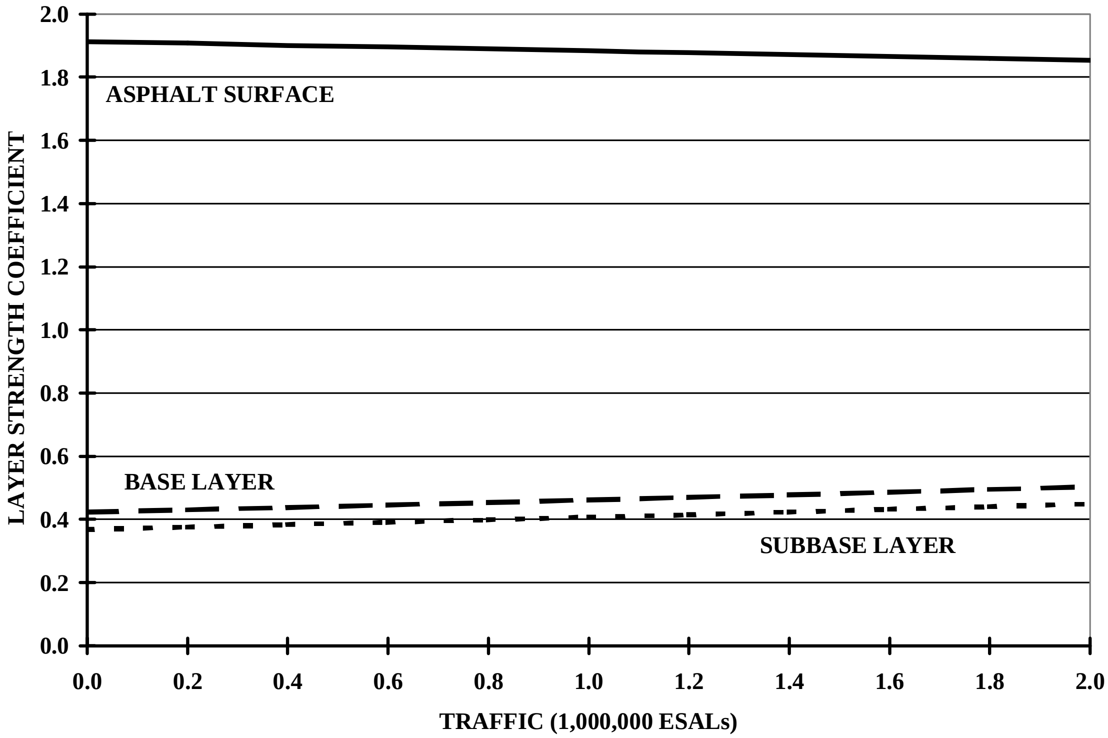

Figure 4.6: Change in the value of the strength coefficients with traffic.

The two most important aspects of this modified model are that (i) it allows the estimation of parameters that can be directly correlated to strength parameters determined in the laboratory based on initial conditions, and (ii) it assesses the extent of the change of the strength of the various layers with traffic.

Table 4.3: Estimated parameters for the modified model.

Parameter	Estimated value	Asymptotic t-value
β_1	4.26	159.6
β_2	-1.59	-9.6
β_3	-0.867	-9.1
β_4	1.91	14.2
β_5	0.423	11.1
β_6	0.368	11.0
β_7	-2.91	-32.7
β_8	-0.167	-45.1
β_9	-0.458	-37.5
β_{10}	0.537	28.9
β_{11}	1.88	91.2
β_{12}	3.99	56.1
β_{14}	-0.0157	-2.6
β_{15}	0.0869	2.1
β_{16}	0.0993	3.1

Chapter 5: Specification and Estimation of the Roughness Models Based on Multiple Data Sources

To achieve the research goal established in Chapter 1, the second objective - the joint estimation of the parameters of the model specification by combining multiple data sources – is addressed in this Chapter. The principles of joint estimation are described in Section 5.1, and a description of the new data sources in provided in Section 5.2. The formulation of a measurement error model, which accounts for the fact that different indicators of riding quality are available in the two different data sets, is presented in Section 5.3. Section 5.4 describes the specification and the estimation of the joint model, while the estimated results are discussed in Section 5.5.

5.1 Joint estimation

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

$$r_E = h(\theta, x, \theta_E, x_E) + \varepsilon_E \qquad (5.1)$$

$$r_F = h(\theta, x, \theta_F, x_F) + \varepsilon_F$$

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. This objective function depends on the assumptions made about the specification form and the data. In the case of generalized least squares (GLS), the objective function is given by the weighed sum of the squared residuals.

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 (Equation (5.1)) are uncorrelated. For the AASHO Road Test data set and the MnRoad Project data the error terms are independent and, therefore, uncorrelated. Under the maximum likelihood assumptions, the joint estimation of the set of Equations (5.1) is achieved by minimizing the joint log-likelihood function.

The first application of joint estimation within the context of pavement performance was carried out by Archilla and Madanat (2001). Previously, Ben-Akiva and Morikawa (1990) applied the same technique to combine revealed and stated preference data to model travel mode choice. The above authors identified the main advantages of using the technique as follows:

(i) Identification

(ii) Bias correction

(iii) Efficiency

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.

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): $\beta_k^E = \lambda_k \beta^F_k$. By applying joint estimation, the true parameters λ_k and β_k can be estimated simultaneously with the rest of the parameters.

Efficiency. If the deterioration process described by the set of Equations (5.1) 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.

5.2 Minnesota Road Research Project (MnRoad)

The Minnesota Road Research Project 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 (Gardiner and Newcomb, 1997). The test set up comprises both experimental test sections and in-service pavement sections (field sections). The full experiment consists of 3 miles (4.8 km) of two-lane interstate (also referred to as the High Volume facility) and a 2.5 miles (4.0 km) closed-loop test track (also referred to as the Low Volume facility).

The estimated traffic on the 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, which routinely collects environmental data. During the winter and early spring months, the depth of frost penetration is monitored using soil resistivity probes.

Table 5.1: Axle load distribution for the experimental traffic at MnRoad.

Axle number and type	Axle weight
Axle 1: steering axle	12,000 lb (53.3 kN)
Axle 2: front axle of tractor tandem	16,900 lb (75.1 kN)
Axle 3: back axle of tractor tandem	16,600 lb (73.8 kN)
Axle 4: front axle of trailer tandem	15,600 lb (63.9 kN)
Axle 5: back axle of trailer tandem	18,400 lb (81.8 kN)

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 per cent overloaded truck whose total weight is 102,000 lb (453 kN). The tractor has an air suspension system and the trailer has four-spring tandem suspension or short rockers (Dai and Van Deusen, 1998). The axle load on the legally loaded truck is distributed as indicated in Table 5.1.

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 five- and ten-year design life, respectively. Both the five- and the ten-year mainline sections have PCC and AC test cells. However, only the data corresponding to the flexible pavement cells is 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. Two different binder types were used at MnRoad: a 120/150 penetration grade asphalt and an AC 20 viscosity grade asphalt. The aggregate was a combination of crushed granite and river gravel, which were the same for all mixes.

The cells corresponding to the 5-Year Mainline (numbered 1 to 4) had a surface thickness ranging from 5.75 to 9.75 inches (145 to 295 mm) while the cells corresponding to the 10-Year Mainline (numbered 14 to 23) had a surface thickness ranging from 7.75 to 25.75 inches (195 to 645 mm). The aggregate base for these cells had a maximum thickness of 37 inches (925 mm). The test cells on the low traffic facility corresponding to flexible pavements (numbered 24 to 31) had thicknesses ranging from 3 to 14 inches (75 to 350 mm), while the corresponding aggregate base had a maximum thickness of 12 inches (300 mm). Four different material types were used for the untreated granular base and subbase layers. The characteristics of these materials comply with MnRoad specifications for materials Classes 3, 4, 5, and 6.

Some of the structural sections are built on a silty-clay which is the native soil at the site, while others are constructed on an imported sandy subgrade. The silty-clay material is similar to the soil at the site of the AASHO Road Test.

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 and can be fully exploited by the application of joint estimation.

5.3 Measurement Error Model

The necessary condition for the application of joint estimation is that both models represented by Equations (5.1) 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 common parameters make joint estimation feasible, while uncommon parameters enable the identification of the effect of new variables.

Traffic on the High Volume facility is not experimental, but it is actual highway traffic diverted from Interstate 94. Unfortunately, the raw traffic data information from this portion of I-94 is not available. Only aggregate information in terms of ESAL is available. The determination of the number of ESALs is based on the AASHO approach, which takes into account the axle configuration and the pavement strength.

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). Riding quality for the MnRoad Project is assessed in terms of roughness by means of the International Roughness Index (IRI). However, a 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:

$$r = 5.5 \ln\left(\frac{5.0}{p}\right) \tag{5.2}$$

where

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

The relationship given in Equation (5.2) and represented graphically in Figure 5.1 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 ninety five percent of the serviceability is explained by the variance of the surface profile (Haas et al, 1994).

The relationship between roughness and serviceability has been investigated by many other researchers who independently agreed that a relationship exists between these two indicators of riding quality (Janoff et al, 1985; Paterson et al, 1989; Haas et al, 1994). Besides, the relationship between roughness and serviceability (given in Figure 5.1) is very accurate in the range of generally accepted serviceability values, i.e., 4.5 to 1.5 PSI.

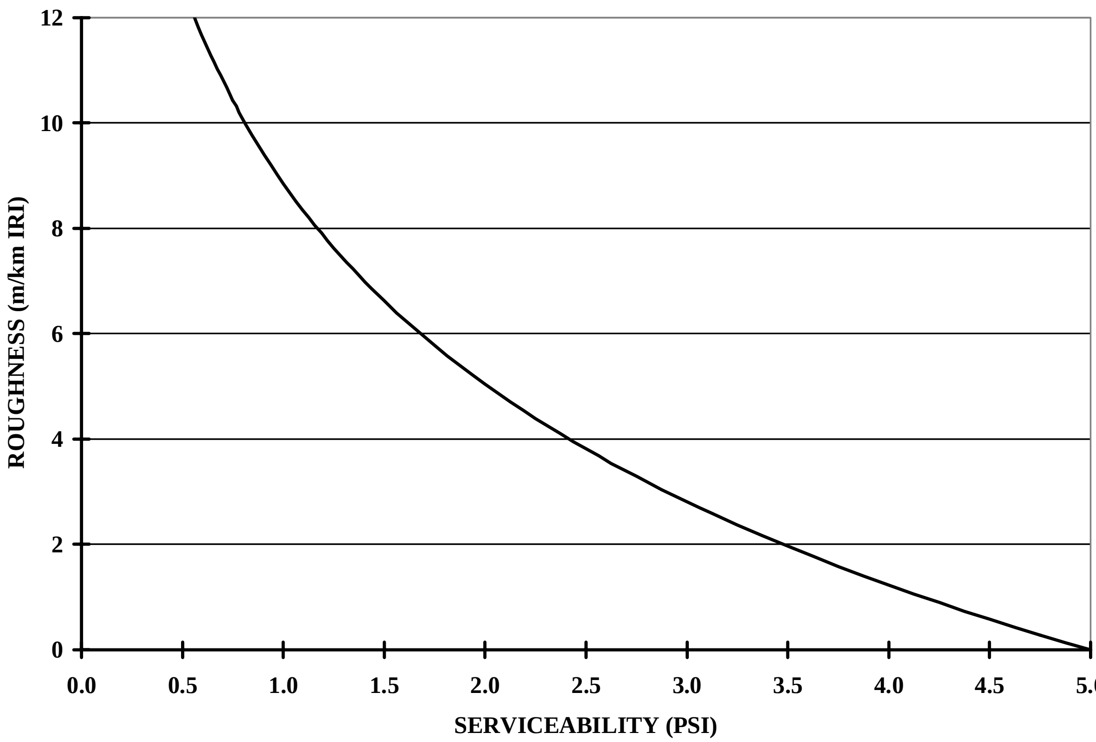

Figure 5.1: Empirical relationship between roughness and serviceability after Sayers, Gillespie and Queiroz (1986).

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 Equation (5.2)) is used as the dependent variable. An error is thus introduced into the model. This error is referred to as the measurement error because of its analogy to the measurement error model (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:

$$y_1 = h(X,\theta) + \varepsilon_1 \qquad (5.3)$$

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

$$y_2 = h(X,\theta) + \varepsilon_2 \qquad (5.4)$$

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 Equation 5.2), so:

$$y_1^* = y_1 + \varepsilon^* \tag{5.5}$$

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 Equation (5.3) are uncorrelated with ε^*. Under this assumption the final joint model is:

$$y_{1,2} = h(X, \theta) + (\varepsilon + \varepsilon^*) \tag{5.6}$$

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.

5.4 Specification of the joint model

The joint model specification is based on the specification of the serviceability model described in Chapter 3 and the relationship given by Equation (5.2). However, the joint specification for riding quality is given in terms of roughness rather than serviceability as in the model described in the previous chapter.

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 Equation (3.14). 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:

$$r_{it} = \theta_1 e^{\theta_2 H_{1i}} + \sum_{l=0}^{t-1} \theta_3 EAT_i^{\theta_9} e^{\theta_{10} G_l} N_{il}^{\theta_{11}} \Delta N_{i,l+1} \tag{5.7a}$$

$$EAT_i = 1 + H_{1i} + \theta_4 H_{2i} + \theta_5 H_{3i} + \theta_6 H_{4i} + \theta_7 H_{5i} + \theta_8 H_{6i} \tag{5.7b}$$

where

r_{it} : roughness (in m/km IRI),

EAT : equivalent asphalt thickness,

H_j : layer thickness,

G : frost gradient, and

θ_j : parameters to be estimated.

Where $N_{il} = \sum_{q=0}^{l} \Delta N_{iq}$, 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:

$$\Delta N_{iq} = n_{iq}\left(\left(\frac{FA_i}{\beta_{12}\,18}\right)^{\theta_{14}} + m_{1i}\left(\frac{SA_i}{18}\right)^{\theta_{14}} + m_{2i}\left(\frac{TA_i}{\beta_{13}\,18}\right)^{\theta_{14}}\right) \tag{5.7c}$$

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.

In the case of the MnRoad High Volume Road (Mainline Experiment) the number of ESALs is determined by converting the observed ΔN_{iq} by means of a multiplicative bias correction factor as follows:

$$\Delta N_{iq} = \beta_{15}\ \Delta ESAL_{iq}^{M} \tag{5.7d}$$

Where $\Delta ESAL^{M}_{iq}$ is the observed number of ESALs for section i and period q at the MnRoad High Volume Road facility. The estimation of $\Delta ESAL^{M}_{iq}$ 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 research (Equation 5.7c). The AASHTO approach assumes different standard axle loads and different exponents from the ones estimated by applying Equation (5.7c). However, for a given observed traffic spectrum, a multiplicative factor is sufficient to capture the difference.

5.5 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 5.2.

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 five percent level so the unobserved heterogeneity cannot be ignored.

Table 5.2: Parameter estimates of the 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

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 five percent significance level.

The estimated standard error of the regression $\left(\sqrt{\hat{\sigma}_\varepsilon^2 + \hat{\sigma}_u^2}\right)$ 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 Figures 5.2 and 5.3. It should be noted that the data of the AASHO sections represented in Figures 5.2 and 5.3 were not used for the estimation of the parameters.

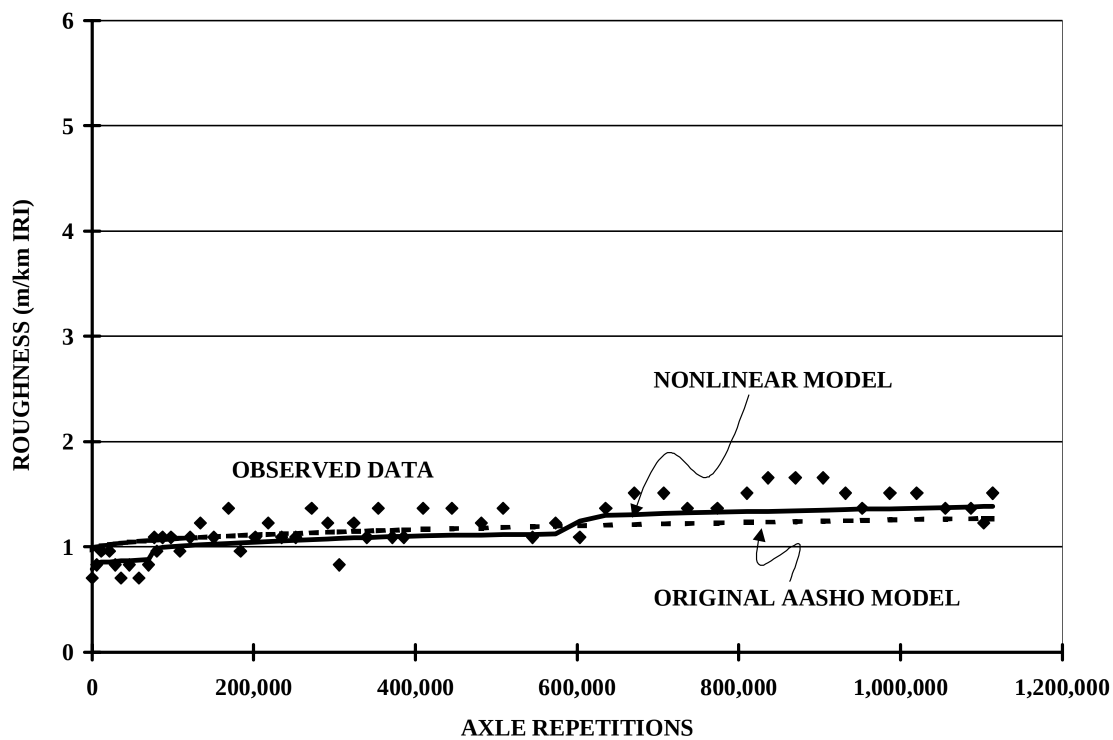

Figure 5.2: Observed versus predicted performance by the linear and the nonlinear models for a pavement section not used in the estimation sample (6,000 lbs single rear axle)

A relatively weak pavement section subjected to light traffic is represented in Figure 5.2. 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 (Figure 5.3).

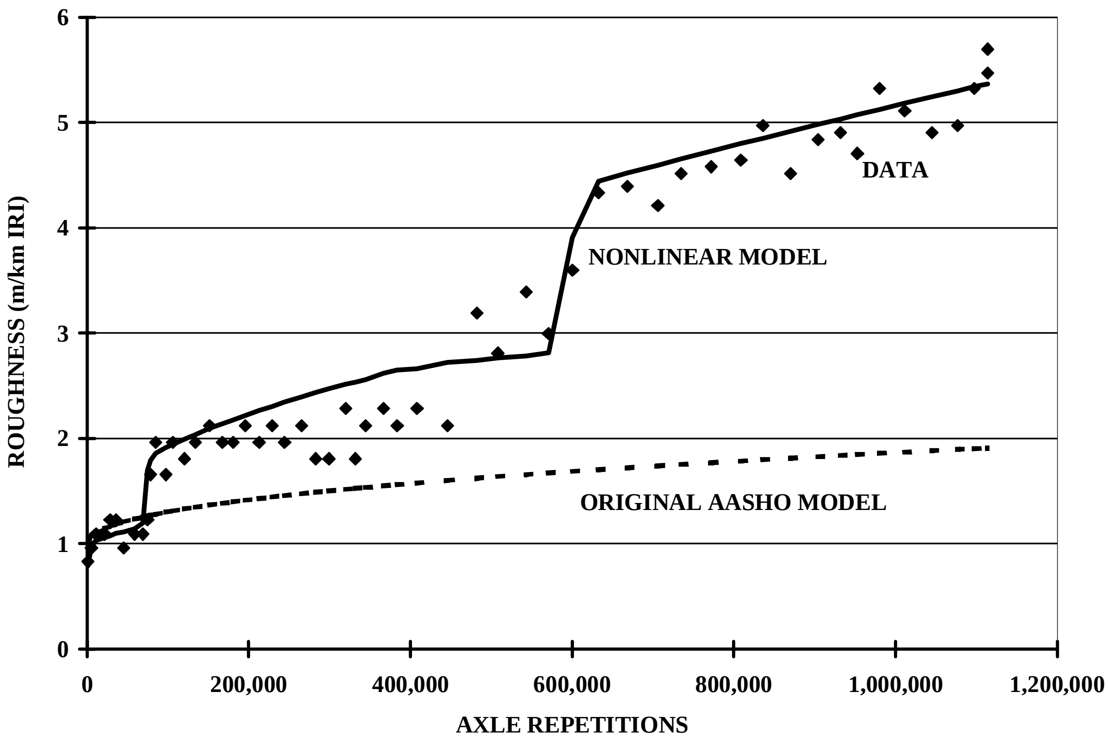

Figure 5.3: Observed versus predicted performance by the linear and the nonlinear models for a section not used in the estimation sample (24,000 lbs tandem rear axle).

Another important aspect of the nonlinear model is its ability to predict the critical phase (Figure 5.3). The critical phase corresponds to the thawing period characteristic of the spring months. During this period, the water, which was trapped during winter within the untreated granular layers in the form of ice, unfreezes. This results in excess moisture present under the asphalt surface layer providing weak support to the surface. Under this critical condition the deterioration of the pavement section takes place at a significantly higher rate. This can be observed in Figure 5.2 and, especially, Figure 5.3.

5.6 Discussion of results

Several of the parameter estimates given in Table 5.2 have an equivalent counter part in the serviceability model discussed in Chapter 4. It is important to note that the corresponding equivalent parameter 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 5.3.

Table 5.3: Comparison of corresponding parameters (for the determination of equivalent traffic) of the 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

The largest difference in the estimated values of these three parameters is approximately seven percent (Table 5.3). This corresponds to the exponent of the power law. 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 allocates more weight to the higher traffic axle loads (greater than 18 kips), while the value 3.85 places more weight on the lighter traffic axle loads (smaller than 18 kips).

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. This approach is compatible with the traditionally used structural number (SN) developed during the original analysis of the AASHO Road Test (HRB, 1962; AASHTO, 1981, 1993).
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 Mn/Road test sections (Table 5.4).

In the MnRoad Project, two asphalt binders were used for the surface layer (AC 120/150 and AC 20), and four different untreated 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 sub base quality materials. The estimated parameters for these three material groups are 1.82, 0.288 and 0.236 (Table 5.4). According to these estimates, the asphalt mixtures used in MnRoad are 82 percent more effective than the asphalt mixture used in the AASHO test in terms of protecting the pavement structure against roughness damage. Accordingly, one inch of base and subbase quality materials is approximately 29 and 24 percent as effective as one inch 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 percent as compared to 24 and 20 percent, respectively, of the materials used at the AASHO test. Both differences are statistically significant at a 10 % level.

Table 5.4: Comparison of corresponding layer strength of the materials used at the 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.

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 High Volume facility underestimates the equivalent traffic by a factor of approximately four. 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 is based on serviceability rather than roughness. 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. Besides, the suspension of the heavy vehicles used today are more pavement-friendly than those used in the 1960s.

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 Figure 5.4 for three different equivalent asphalt thicknesses (4, 6, and 8 inches) and three different frost gradients (-2, 0 and +2 inches 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.

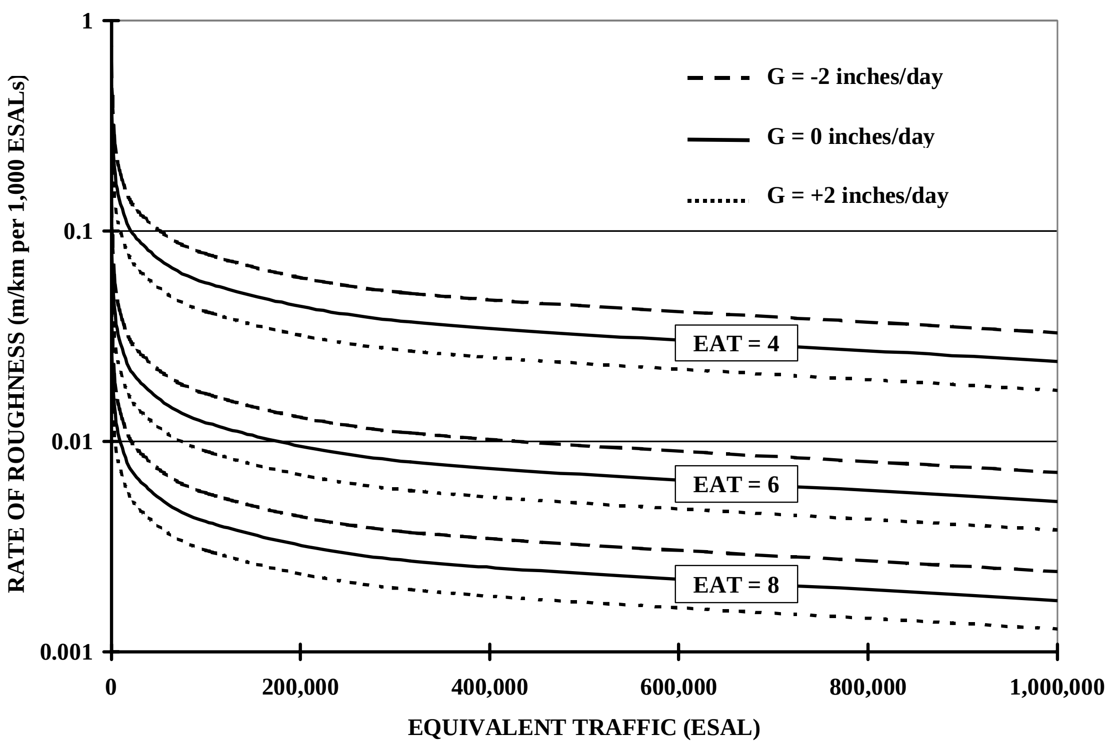

Figure 5.4: Variation of the rate of roughness increase as a function of traffic, pavement strength and environmental conditions.

Chapter 6: Conclusions and recommendations

6.1 Concluding remarks

Most models described in the literature attempt to predict the deterioration of the riding quality as a dependent pavement performance indicator based on relationships with a number of explanatory variables such as traffic loading, pavement strength, and environmental factors. However, most available models have one or both of the following limitations:

(i) ***Inadequate specification form*** that has inherent limitations (i.e. linear models) or that is not based on sound physical principles.

(ii) ***Inadequate parameter estimation methods*** because of the failure to recognize some of the problems with the data set or the use of wrong estimation techniques.

Many authors follow a ***best-fit*** approach to determine the specification form with little concern for the physical cause of the deterioration process itself. It is often found that relevant variables are omitted from a given specification because the estimated t-statistics are low.

Many models, without any apparent reason, are constrained to a form that is a linear combination of the available regressors (or some nonlinear transformation of the regressors). This is often the case, even though there is enough evidence that relationships between riding quality and relevant explanatory variables are by no means linear. These issues result in models that suffer from important specification biases.

Another source of specification bias results from the use of traditional forms, which are often not applicable. For instance, a common assumption made by most road damage prediction models is the validity of the fourth power law to determine equivalent traffic.

Among the second type of problems - those related to incorrect parameter estimation methods - the most common concern relates to the generalized use of ordinary least squares, even when unobserved differences between pavement sections are important and have a significant effect on pavement deterioration.

Other problems that usually lead to biased models are the use of endogenous variables as explanatory variables, and the problems associated with unobserved events typical of pavement performance data sets.

The above discussion emphasizes the three most important aspects that need to be taken into account when estimating pavement performance models:

(i) A ***physically realistic model*** specification,

(ii) An ***adequate data source***, and

(iii) Statistically ***sound estimation techniques***.

A robust theoretical background should be support the model specification. The data should be obtained from a well-conceived experimentally designed test, aimed at addressing all the important variables that have been identified during the development of the theory. Unfortunately, this is seldom the case. Therefore, it is up to the modeler to take into account these limitations to develop mechanistically correct models.

This research proved the importance of the three aspects mentioned above. A nonlinear 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, reduced by half. 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.

6.2 Concluding comments on the joint model

A number of empirical models for predicting riding quality were developed as part of this dissertation. In Chapter 4, three different models are presented to estimate pavement serviceability (in PSI) as a function of pavement structural characteristics, axle traffic configuration and load, and environmental variables. These models were estimated based on the data from the AASHO Road Test. In Chapter 5, the basic model presented in Chapter 4 was updated using joint estimation. The updated model estimates 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. The main advantages of joint estimation are:

(i) The effect of variables not available in the first data source can be identified and quantified.

(ii) The parameter estimates are efficient (minimum variance) because multiple data sources are pooled together.

(iii) Bias in the parameters can be identified and corrected.

(iv) Different measurements of the same property can be incorporated into the model by introducing a measurement error model.

The jointly estimated model fits the data very well. For instance, the regression error of the jointly estimated model is less than half that of the equivalent linear model. The most important characteristics of the joint model (updated model) can be summarized as follows:

(i) The updated model was developed primarily for the management of the road network. Within a pavement management context, predictions are usually required only for the following time period. Hence, the model predicts roughness incrementally, i.e., roughness at time t is the sum of predicted roughness increments over time intervals Δt.

(ii) The estimated exponent of the power law (3.85) indicates that currently used values (4.0-4.2) overestimate the equivalent traffic of the higher load (>18,000 lbs) classes, but underestimate the equivalent traffic of the lower load classes (<18,000 lbs). This is important since most highway traffic is mainly composed of light traffic. It is important to emphasize that this estimate is based on considerations of deterioration in terms of riding quality under given environmental conditions. When other performance indicators are used, the exponent is expected to differ substantially. The exponent of the power law forms the basis for the allocation of cost responsibilities for pavement deterioration to the different load classes.

(iii) 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 lbs single axle with dual wheels. The estimated values are 9,400 and 33,000 lbs, respectively. Thus, the practice of using the same equivalent load for different axle configurations should be avoided to prevent gross estimation errors of equivalent traffic. Besides, the equivalent loads are necessary to establish the allocation of cost responsibilities for pavement deterioration to the different axle configurations.

(iv) 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 allows 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. It should be noted that the estimated parameters indicate that quality of the materials used at the MnRoad Project are significantly superior to that of the materials used at the AASHO Road Test The equivalent asphalt thickness concept applies within reasonable boundaries of typically used surface, base and subbase layers.

(v) 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 although the initial roughness decreases as the thickness of the asphalt surface increases, it never reaches the maximum theoretical value of 0.0 m/km IRI.

(vi) The model indicates that, ceteris paribus, the rate of roughness progression decreases with traffic. However, there are other variables that should be accounted for when considering the overall roughness progression, e.g., the frost gradient.

6.3 Model limitations and future research

Like any other deterioration model, the model developed in this dissertation 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 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. Some of the limitations are described in the following paragraphs.

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 regions of markedly different characteristics, e.g. California. A possible approach to overcome this limitation would consist of obtaining another data source (corresponding to the new regions) and updating the models by applying joint estimation once again.

This is, indeed, a very logical next step in this line of research. The data in the Pavement Management System of each state could be a reasonable alternative data source. The data collected as part of the Long-Term Pavement Performance (LTPP) 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 more important potential biases could be determined and corrected.

An important limitation of this model is that it failed to identify the effect of other relevant environmental variables, such as temperature. Temperature affects the stiffness of the asphalt mixture and, therefore, the strength of the pavement, which in turn determines the deterioration rate. However, the temperature information available in the data sets used was not precise enough to characterize this effect.

The model estimation approach assumes that, except for the intercept term, the model parameters are constant. An alternative approach would be to assume that some of the parameters of the specification are not constant, but rather randomly distributed across pavement sections. Under this new assumption, the random coefficients estimation approach would produce parameter estimates of minimum variance (efficiency). This could be the case for the layer strength parameters due to construction variability typical of highway pavements.

Finally, these limitations are a characteristic of the specific model. However, this dissertation 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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