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By Eleni Bardaka

Entitled
Mixed Linear Modeling Techniques for Enhancing Pavement Performance Predictions

For the degree of Master of Science in Civil Engineering

Is approved by the final examining committee:

Samuel Labi
Chair

Kumares C. Sinha

Fred L. Mannering

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# MIXED LINEAR MODELING TECHNIQUES FOR ENHANCING PAVEMENT PERFORMANCE PREDICTIONS

A Thesis

Submitted to the Faculty

of

Purdue University

by

Eleni Bardaka

In Partial Fulfillment of the

Requirements for the Degree

of

Master of Science in Civil Engineering

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West Lafayette, Indiana

To my god-daughter, Ευδοκία, who is the source of hope and power in my life.
No distance can make your light fade away.

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# ABSTRACT

Bardaka, Eleni. M.S.C.E., Purdue University, August 2012. Mixed Linear Modeling Techniques For Enhancing Pavement Performance Predictions. Major Professor: Samuel Labi.

The use of appropriate advanced modeling techniques for predicting the performance of pavements that have received rehabilitation treatments may reap substantial benefits to a Pavement Management System (PMS). If the modeling technique is appropriately chosen on the basis of practicality, precision, the intended use of the model, and the nature of the pavement data, its applicability to PMS can be enhanced greatly. Pavement rehabilitation data typically constitutes of repeated measurements that form an unbalanced three-level nested structure, which makes the analysis quite challenging. This thesis proposes an enhanced methodological framework for pavement rehabilitation treatment analysis that uses mixed linear modeling techniques. Mixed models constitute a statistical technique that includes both fixed effects and random effects. The proposed framework is demonstrated using data from the Indiana Interstate network. In applying the developed framework, agencies can not only statistically quantify the post-rehabilitation performance of pavements, but also develop estimates and ranges of treatment service lives and thus update or refine the treatment service lives that are currently published in their pavement design or preservation manuals. These procedures are demonstrated analytically using a case study. The proposed framework can also be used by highway agencies as part of their network-level needs assessment because it offers a more reliable estimation of future physical and fiscal needs, as shown in the case study presented in this thesis.

# CHAPTER 1 INTRODUCTION

## 1.1 Background and Problem Statement

Highway assets constitute the most valuable public-owned infrastructure in most countries and are a vital factor in economic growth and social development. Of the various improvement activities applied to highway infrastructure in the United States, highway pavement preservation is associated with the highest levels of expenditure. Preservation treatments involve the structural or functional enhancement of the pavement structure in order to improve the condition and ride quality of the pavement and to extend the life of pavement assets. The importance of maintenance and rehabilitation activities for maintaining pavement assets in a serviceable condition have been emphasized by federal regulation; and the 1991 Intermodal Surface Transportation Efficiency Act allocated the highest percentage (35%) of federal highway funds to pavement preservation activities (FHWA, 1997). In spite of federal funding assistance, highway agencies still face budgetary constraints in preserving their pavement assets, under the combined stress of ever-increasing personal and commercial traffic and climate. For these reasons, pavement managers try to identify and implement cost-effective preservation strategies and practices; and pavement managers need reliable pavement performance prediction tools and preservation treatment service life estimates to support their decision-making.

In a pavement management system (PMS), tools and methods are deployed to determine optimum strategies for providing, evaluating, and maintaining pavement assets in a serviceable condition (AASHTO, 2001). Mathematical models that predict the future condition of a pavement on the basis of past deterioration trends constitute a major part of the set of tools deployed by pavement managers. *Pavement preservation* is the sum of activities undertaken to provide and maintain serviceable highways, and typically includes corrective maintenance, preventive maintenance and rehabilitation projects (Ong et al, 2010). Highway agencies are incorporating the analysis of preservation treatments performance in pavement management for multiple reasons. Treatment performance models, for project-level planning purposes, can be used for the short-term and long-term prediction of the condition of specific pavement sections after they receive a specific treatment. Numerous ways of measuring the effectiveness of preservation treatments, both in the short-term or long-term, have been proposed. However, the most widely-accepted approach is measuring the time that passes after a treatment application until pavement performance reaches a specified threshold, which is referred to as the *treatment service life* (Sinha and Labi, 2012). Using preservation performance models, pavement managers can obtain treatment service life estimates and make inferences about treatment effectiveness. This information further helps the highway agency to carry out effective decision-making for future treatment applications, determine optimal times for preservation interventions and deploy preservation strategies that minimize pavement life-cycle cost, thus enhancing the pavement management operation (Sinha and Labi, 2012).

Pavement management can be developed and practiced at two levels: network and project (Haas et al, 1994). Network-level management is associated with physical and monetary needs assessment, programming, and budgeting for a pavement network; while project-level management focuses on applying optimal design or preservation strategies for a specific pavement section (FHWA, 1995). Integrating the pavement management network and project levels for achieving optimal holistic system operation were identified as a key challenge by Haas (1995). Two major prerequisites for this integration to occur are: (1) the development of one central database for the PMS, and (2) the integration of performance models, which means using one methodology suitable for both network and project management levels (Pilson and Hudson, 1998). Figure 1.1 illustrates the possible roles of integrated preservation performance modeling in pavement management.

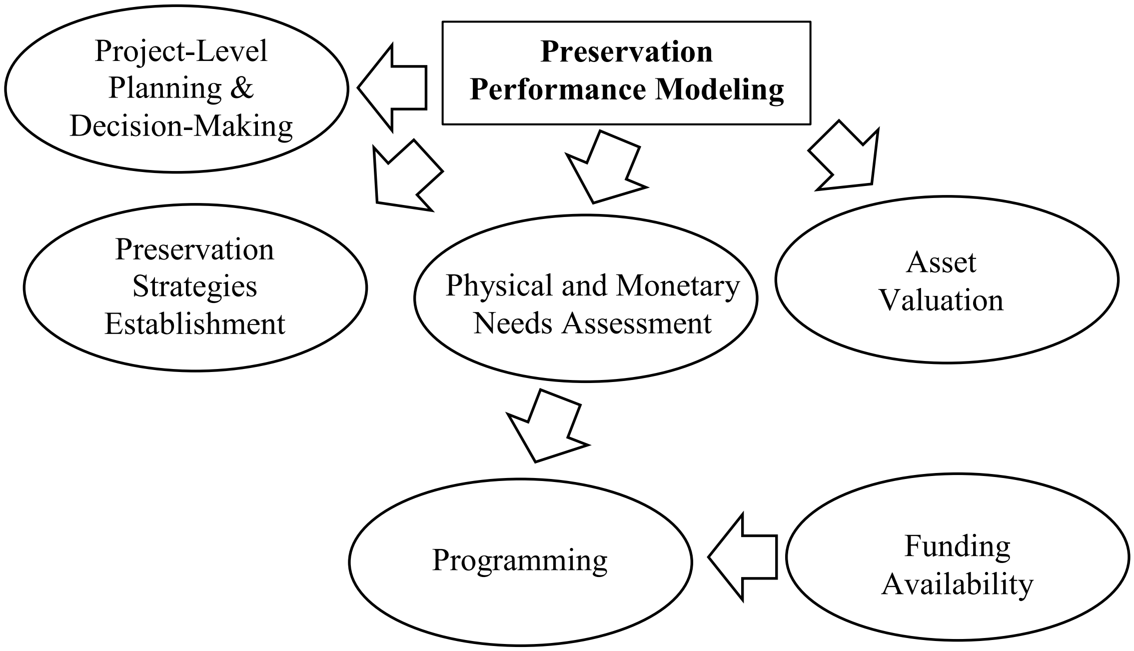


Figure 1.1 Applications of Integrated Preservation Treatment Performance Modeling in Pavement Management Processes

Through an integrated process, preservation performance models, apart from project-level predictions, can help establish the year in which asset preservation likely will be necessary, which then can be used to establish short- or long-term physical and fiscal work plans; they can also offer reliable treatment life expectancies, which can be used to develop improved preservation strategies. Integration of asset valuation performance-based or age-based approaches with the project and network levels of management can also be accomplished using performance predictions.

Reliable and effective preservation treatment performance modeling techniques that allow for network-level and project-level integration may bear substantial benefits to a PMS. Increased precision in terms of predictions and treatment service life estimates can improve treatment selection decision-making and reduce the uncertainty in the estimation of network-level physical needs, and thus, in programming and budgeting. The incorporation of performance modeling techniques in PMS was initiated in the 1970s.

Since then, a variety of techniques have been investigated for use or implemented in PMS. However, in the area of preservation performance, there is a need for an enhanced framework for preservation performance prediction that can accommodate the peculiar nature of pavement data and allow for integration of the network and project management levels, while remaining practical and appropriate for PMS application.

## 1.2 Study Objectives

The main objective of this study is to develop a methodological framework for preservation treatment performance analysis for pavement management. The framework duly considers the peculiar nature and structure of pavement preservation data, the need for reliable predictions in PMS, and the purposes and integration requirements of pavement management. In applying the developed framework, agencies can statistically quantify the future performance of pavements that have been preserved and also of pavements slated for specific preservation treatments. Another study objective is to provide a methodology by which agencies can develop estimates and ranges of treatment service lives. Moreover, this thesis seeks to identify specific modeling formulations appropriate for modeling preservation treatment performance and thus facilitate the adoption of the proposed framework by pavement managers. Another objective is to analytically demonstrate the modeling technique and the procedure of predicting performance and estimating treatment service life through case studies. Finally, this thesis seeks to examine the impact of the proposed methodology on physical and monetary needs prediction at the network level.

## 1.3 Scope of the Study

This thesis focuses on *pavement rehabilitation*, which involves structural or functional pavement enhancement often by adding an overlay to a pavement structure in order to improve pavement condition and serviceability, and, more importantly, to extend pavement service life. The data used for illustration and configuration of the proposed methodology are from a selection of rehabilitation treatments and one preventive maintenance treatment, which had been applied to Indiana Interstates during the period 1996-2006. The treatments examined are: (1) thin HMA overlay, (2) structural HMA overlay, (3) functional HMA overlay, (4) crack and seat PCC and HMA overlay, (5) repair PCC and HMA overlay, (6) rubblize PCC/Composite and HMA overlay, and (7) PCC overlay on PCCP. As a pavement performance indicator, the International Roughness Index (IRI) is used; however, the proposed methodology can accommodate any indicator that is or can be considered a continuous variable. Pavement performance and traffic data for the period 1995-2009 were used. Finally, the physical and monetary needs assessment considers only the future rehabilitation needs of the Indiana Interstates that were rehabilitated during the period 1996-2006.

## 1.4 Study Outline and Organization

In this thesis, a general framework for conducting asset preservation analysis and identifying an optimal methodology for incorporation in an asset management component system was followed (Figure 1.2).

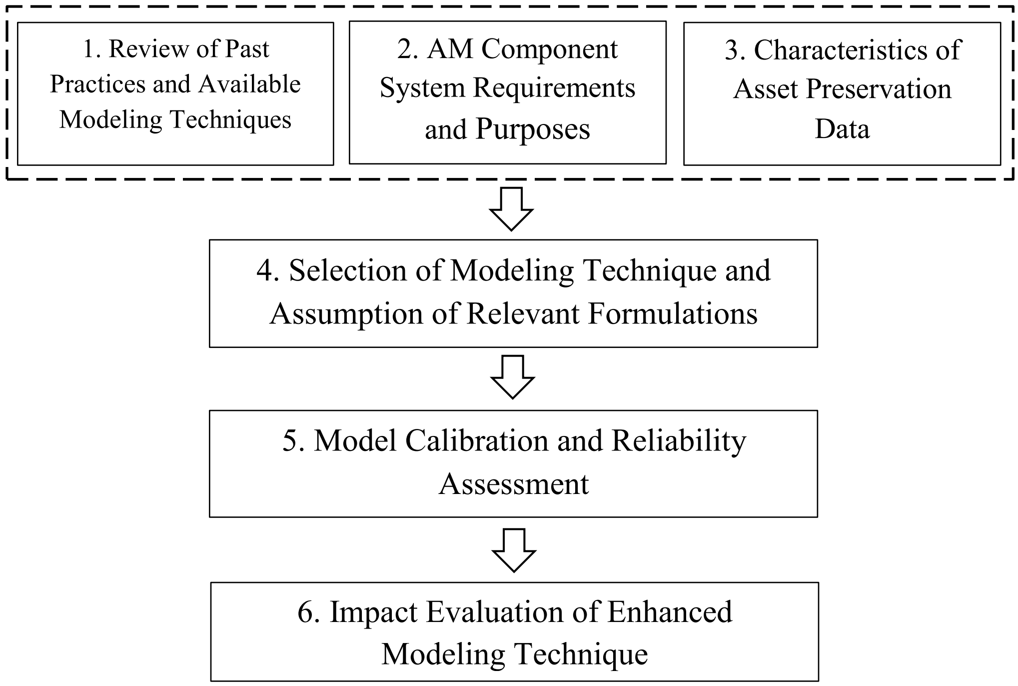


Figure 1.2 General Framework for Developing a Methodology Regarding Asset Preservation Treatment Performance

This general framework was followed throughout the five chapters of this thesis. The first step, which requires the review of past practices and available modeling techniques, is accomplished in Chapter 2, where the state of practice and state of the art techniques and methods for predicting pavement deterioration and treatment service life are reviewed. The contribution of rehabilitation treatment performance models in providing input data for PMS (second step) and the characteristics of pavement rehabilitation data (third step) are presented in the beginning of Chapter 3. The fourth step of the general framework is partly accomplished in Chapters 2 and 3. The modeling technique theory and the development of suitable formulations are presented in Chapter 3, along with the methodology application in the form of a case study, evaluation of the results in terms of general model fit and predictability, and the methodology configuration (step 5). The proposed methodological framework for rehabilitation treatment performance prediction is presented at the end of Chapter 3. The sixth step of the general framework shown in Figure 1.2 requires, in the context of this study, evaluation of the impacts of the proposed methodology on the other pavement management processes, under the assumption that the proposed methodology is used to accomplish integration. Chapter 4 presents the impacts of the proposed methodological framework on future rehabilitation needs estimation under two approaches: (a) age-based needs assessment, and (b) performance-based needs assessment. Chapter 5 summarizes and concludes this thesis and provides recommendations for future research.

# CHAPTER 2 A SYNOPSIS OF METHODOLOGIES FOR PAVEMENT DETERIORATION PREDICTION

## 2.1 Literature Review of Empirical Modeling Practices

Attempts to develop mathematical equations to describe and predict pavement damage initiated in the late 1950s with the beginning of the AASHO Road Test (HRB, 1962). Then, in the 1970s, researchers began incorporating pavement deterioration models in Pavement Management Systems (PMS) because deterioration models constituted an essential part of the early pavement management processes. A variety of modeling techniques have been investigated or implemented in PMS. This section presents a literature review of the state of the practice and state of the art techniques and methods for predicting pavement deterioration and/or for estimating treatment service life in order to identify their possible limitations and areas for improvement. The review also includes existing empirical techniques that are not yet employed in agency PMSs in order to identify possible benefits that could be realized by highway agencies in applying these techniques.

### 2.1.1 Deterministic Models

#### 2.1.1.1 Univariate Curve Fitting

Fitting a curve to pavement performance or condition data involves the establishment of a linear or non-linear function to describe the relationship between pavement performance and a dynamic (cumulative, time related) variable, which could typically be related to age or accumulated traffic among other attributes. The relationship may be purely empirical, purely based on a theoretical model, or a combination of the two. The difference between simple curve fitting and regression methods is that in the former, there is little or no investigation of what affects the deterioration process and the manner of such influence (i.e., the form of the deterioration curve); and a function is pre-assumed and the parameters are estimated typically with least squares. Most highway agencies have deployed curve fitting because of its simplicity and because it is practical for them to use. The Illinois DOT, for its PMS software, uses linear functions to predict pavement condition based on current condition as follows (Bham et al, 2003):

$$\text{Future Condition} = \text{Current Condition} + a(\text{Years}) \tag{2.1}$$

where $a$ is the deterioration rate, Years is the pavement age or the age of the last preservation treatment applied. The deterioration rate is defined for each pavement family; and curve fitting can be used to estimate the rate. The Washington State DOT incorporated curve fitting, which uses the Levenberg-Marquardt nonlinear least squares estimation, for performance prediction in its PMS software using the following form (Pierce et al, 2004):

$$\text{Pavement Structural Condition} = a - b(\text{Age})^c \tag{2.2}$$

The Louisiana Department of Transportation and Development uses similar equations for obtaining predictions for a variety of performance indicators (Khattak et al, 2008). For different performance indicators, different functional forms are assumed to predict pavement condition as a function of age. The Utah DOT uses the dTIMS software for pavement condition modeling that assumes the following curve (UDOT, 2009):

$$\text{Present Condition Index} = 100 - x(\text{Age})^2 \tag{2.3}$$

The last of the agencies considered in this review, the Minnesota DOT, uses historical data on a pavement smoothness index, called the Ride Quality Index, to fit a curve for each pavement section and to define the remaining service life (MnDOT, 2011).

### 2.1.1.2 Multivariate Regression Analysis

Regression analysis produces pavement performance equations based on the assumption that pavement deterioration is caused by multiple factors, such as age, traffic, climate, and maintenance and rehabilitation history. Regression is also used in pavement preservation analysis for the estimation of treatment service life (Labi et al, 2005; Khurshid et al, 2009a; Khurshid et al, 2009b; Irfan et al, 2009a; Irfan et al, 2009b; Ahmed et al, 2010).

Highway agencies have not widely embraced multivariate techniques due to the lack of data. Another reason is the nonexistence of an easily-manageable database system; and although many agencies have been collecting data for over 20 years, their data often cannot be easily organized into a useful format, which inhibits statistical analysis (Lea and Harvey, 2004). Rajagopal and George (1991) developed non-linear performance prediction models for the Mississippi State Highway Department using the Pavement Condition Rating (PCR) as an indicator of pavement condition. They explained the deterioration process using pavement age, traffic, thickness of the last treatment applied, life-cycle before overlay, and a composite structural number. Sebaaly et al (1995) developed performance models for the most commonly-used pavement maintenance techniques of the Nevada DOT. They used regression analysis to predict the Present Serviceability Index (PSI) in terms of pavement age, equivalent single axle loads (ESALs), structural number, maximum and minimum yearly temperature, freeze-thaw cycles, and total number of wet days. Some highway agencies may encounter difficulty in applying models such as the Mississippi and Nevada models because fairly elaborate data on multiple attributes is required by them.

Ong et al (2010) developed regression models for a selection of preservation treatments for the Indiana DOT. The models were developed for three pavement performance indicators (IRI, PCR, and Rutting) and used the cumulative average daily truck traffic and the cumulative annual freeze index to predict pavement deterioration.

The new Mechanistic-Empirical Design Guide (M-E PDG) includes performance models that were estimated using regression analyses. The expectation is that these models will be used – directly or after calibration – by highway agencies (AASHTO, 2008). The proposed methodology is rather complicated. Several equations, which include multiple variables, are developed for different distresses; and some of the distress estimates are then used as input into models for roughness prediction. Aguiar-Moya et al (2011) recognized that this process may introduce bias in the analysis because of possible correlation between the estimated distresses and unobserved components in the roughness performance models. The researchers corrected for this bias by using instrumental variable regression to estimate the performance models. Moreover, it was identified that the pavement data used for the M-E PDG models are panel data, and a random effects model was used to correct for possible unobserved heterogeneity. Nevertheless, the correction of bias still does not make the M-E PDG performance models practical for highway agencies. These models were developed using data from the Long-Term Pavement Performance (LTPP) database and include variables not readily available in most highway agencies databases, such as the soil plasticity index, percent of subgrade material passing No. 200 sieve, and PCC air content (AASHTO, 2008). For this reason, the deterioration models of the ME-PDG are not expected to be widely adopted by highway agencies for purposes of pavement management.

#### 2.1.1.3 Bayesian Regression

Bayesian regression is a specialized adaptation of the Bayes' Theorem involving the development of multivariate regression models that explicitly consider two sources of information: (i) information that is known prior to an experiment and (ii) information that is derived from an experiment (Washington et al, 2011). This approach has been adapted by a number of researchers in pavement management as it allows the development of performance models even where there is insufficient data.

A Bayesian methodology for pavement deterioration modeling designed for highway agencies and accompanied by relevant software was first developed by the Canadian Strategic Highway Research Program (C-SHRP) (Hajek and Bradbury, 1996). The C-SHRP Bayesian methodology includes the development of a linear regression model based on the available observed data, separate models of the same form based on expert judgment, and a method for combining these two sources of information. The methodology and the use of the relevant software were proposed to the Ontario Ministry of Transportation (Hajek and Bradbury, 1996). Kajner et al (1996) tested the methodology for eight Canadian highway agencies and demonstrated that they were practical for use.

George (2000) conducted a study for the Mississippi DOT exploring Bayesian regression for modeling pavement performance. Ten experts established the "prior" data and their judgments (expressed in numerical scores) were encoded using a full-orthogonal matrix elicitation technique. The study concluded that there was large disparity between the field data and the expert opinion; and as a consequence, the regression models also developed in the study were more preferred to the Bayesian regression models.

Recently, Amador and Mrawira (2011) reanalyzed a rut-depth progression model developed in previous research from the AASHO Road Test data using Bayesian regression and concluded that this method produces more reliable performance predictions.

### 2.1.1.4 Autoregressive Models

Autoregressive modeling is a method of describing the behavior of a variable on the basis of its past values, typically used in time-series analysis (Washington et al, 2011). Abu-Lebdeh et al (2003) used this technique for predicting pavement distress development for different preservation treatments and proposed the developed autoregressive models as an alternative prediction tool for the Michigan DOT. Although the researchers concluded that the predictions displayed high accuracy, they conceded that use of the models requires extensive data that may not be available to highway agencies. Prozzi and Madanat (2003) estimated a non-linear autoregressive model using data from the AASHO Road Test and concluded that this technique would be appropriate for pavement management because condition data are typically available on a regular basis and predictions are commonly required for the next one or two time periods. However, in reality, pavement management systems are planning tools and the predictions therefore are actually needed for more than one or two time periods. Thus, the use of these models is impractical.

### 2.1.1.5 Seemingly Unrelated Equations (SURE)

In empirical studies, pavement deterioration is typically represented by one performance indicator and modeled as such. However, different performance indicators potentially may be correlated with each other even though they are related to different deterioration mechanisms (Prozzi and Hong, 2008). Effective decision-making in pavement management ideally takes into account various performance indicators. For this reason, researchers have proposed addressing performance models based on different performance indicators as a system of equations, which can capture the correlation of the different indicators and thus provide a more efficient estimation. Prozzi and Hong (2008) first proposed the use of seemingly unrelated equations as an appropriate approach for asset performance modeling. Anastasopoulos et al (2012) followed a similar approach, and using random parameters in order to control for unobserved heterogeneity, provided more precise parameter estimates.

## 2.1.2 Probabilistic Models

### 2.1.2.1 Markov Chains

A Markov chain describes a time-independent stochastic process that undergoes transitions from a state at one stage to a state at the next stage. A model based on this chain describes the probability of transition from one condition state to another. These transition probabilities, based solely on the present state rather than past states, are represented in a matrix form that is called the transition probability matrix (Washington et al, 2011). If the condition of an asset can be classified into discrete states, the deterioration process can be modeled as a Markov chain.

The major challenge for developing Markov models is the establishment of the transition probability matrices. For this reason, the past literature contains a number of ways for calculating these probabilities, such as expert opinion, frequency of observed transition, sampling from statistical distributions, optimization, and Bayesian techniques. Jiang et al. (1988) developed a methodology for estimating the transition probability matrix for bridge performance modeling, whereby an initial guess is made for the transition probabilities and the expected condition rating at each age is estimated. Then, a non-linear regression model is developed to represent the "actual" performance curve. Finally, the transition probability matrix is obtained through optimization with the objective function of minimizing the absolute distance between the "actual" condition rating at a certain age and the predicted condition for the corresponding age generated by the Markov Chain. Madanat et al (1995) used an ordered probit model to construct an incremental discrete deterioration model in which the difference in the observed condition rating is an indicator of the underlying latent deterioration. This model was then used to compute a time-dependent transition probability matrix. Li et al. (1996) used a non-homogeneous Markov probabilistic approach for pavement deterioration modeling. According to the authors' approach, each element of the transition probability matrices is determined on the basis of reliability analysis and Monte Carlo simulation techniques.

Markov chain-based prediction models can be integrated with network programming and prioritization programs to produce optimal preservation treatments, given the performance standards and budgetary constraints (Butt et al, 1994). For this reason, the Markov process for network-level performance prediction in PMS has been adopted by several highway agencies. The Arizona DOT was one of the first agencies to use the Markov process for network level performance prediction combined with linear programming in order to achieve optimal highway preservation (Golabi et al, 1982). Since then, that agency has continuously enhanced the procedures used in the probabilistic performance prediction (Wang et al, 1992; Wang et al, 1994). However, the need for obtaining performance predictions at the project level and network level through an integrated procedure was recently realized, and a site-specific modeling approach was incorporated in the PMS (Li et al, 2006). Although no details were provided about the site-specific approach and its estimation procedure, the inability of the Markov process to produce accurate predictions at the project level was emphasized.

Regarding other highway agencies, Silva et al (2000) proposed the use of the Markov model or the logistic growth model for local PMS in Michigan counties; Chou et al (2008) developed Markov models for Ohio DOT; and Wang et al (2010) developed a Markov process-based management system for the Georgia DOT to forecast their network-level annual budget needs.

### 2.1.2.2 Survival Analysis

Survival analysis, which involves the modeling of time to "failure," has been used by a significant number of researchers for estimating the time it takes for a pavement to deteriorate to a certain performance threshold. In general, the probability that a pavement will not have failed by a certain age *t* is represented by a survival function (Washington et al, 2011):

$$S(t) = P(T \geq t) \tag{2.4}$$

where $T$ is a random variable denoting the time of "failure."

Survival curves can be developed using non-parametric, semi-parametric, or parametric hazard-based duration models. In the non-parametric models, there is no information pertaining to the distribution of the time to failure, $T$, and how the exogenous variables affect the time to failure. In the semi-parametric models, there is also no assumption about the underlying failure distribution, but the effects of potential influential factors on the time to failure can be estimated. Finally, in the parametric models, a distribution of the time of failure is assumed, and the effects of exogenous variables are estimated (Washington et al, 2011).

Unlike deterministic models, duration models enable the stochastic nature of pavement failure to be evaluated, as well as censored data to be incorporated, in the statistical estimation of the model parameters (Prozzi and Madanat, 2000). The term "censored data" refers to the unobserved "failure" events in a dataset, which is a common problem in modeling service life. Some pavement sections will reach terminal conditions during the observed period, while others will fail at some point in the future (Paterson, 1987).

Paterson and Chesher (1986) were the first to apply survival analysis in pavement surface distress data for developing pavement deterioration models for the World Bank. Prozzi and Madanat (2000) reanalyzed the American Association of State Highway Officials (AASHTO) Road Test data using parametric duration models. Romanoschi and Metcalf (2000) used rutting data collected as part of the first full-scale accelerated pavement test in Louisiana to identify appropriate statistical models for determination of the probability distribution function for the time to "failure" of pavement structures. DeLisle et al (2003) focused on the effect of the exclusion of censored data on the estimated service life. The results from their study indicated that if censored data are simply excluded from the analysis, the resulting deterioration rates tended to be greater than the actual rates. Wang et al (2005), using data from the LTTP program, conducted a parametric survival analysis based on the accelerated failure time model to investigate the relationship between fatigue cracking and its potential influencing factors in flexible pavements. Yang (2007) developed parametric duration models using PCR data collected as part of the Florida PMS. Yu et al (2008) also developed survival curves based on historical PCR data using a semi-parametric method called the Cox proportional hazards (PH) method. Recently, Morian et al (2011) used the Kaplan-Meier method to develop survival curves for estimating the service life of the maintenance treatments applied as part of the Specific Pavement Study - 3 (SPS-3) of the LTPP program.

Notwithstanding the extensive research in the area of probabilistic pavement service life estimation, the fact remains that there has been only one application in practice. Gharaibeh and Darter (2003) used data from the fourth round of pavement longevity studies conducted by the Illinois DOT, to investigate pavement service life using survival curves. Survival curves were generated using the Kaplan-Meier method; and mathematical models then were best fitted to the survival curves to predict the probability of failure as a function of age or the cumulative number of ESALs. It should be noted that, for the Gharaibeh and Darter study, service life was defined as the time interval between two successive overlay placements; therefore, this estimate may not reflect the real service life and would likely be influenced by agency budget constraints or the subjective judgment of the decision-makers.

### 2.1.3 Other Model Types

#### 2.1.3.1 Mixed Models

Pavement performance and condition data are typically a cross-section of time-series measurements from different pavement sections, which is also known as panel data. General statistical models for cross-sectional data (e.g., regression, probit, logit, etc.) ignore the panel structure and treat the effect of unobserved variables as a pure chance event (Hsiao, 1993). Mixed models are an extension of the general linear model to allow for random effects and correlation among responses. Random effects are random variables that represent unobserved characteristics shared within the observations of a specific group (pavement section, in the context of this thesis) (Washington et al, 2011). The models are termed "mixed" to reflect the presence of both fixed effects (fixed parameters) and random effects (Littell et al, 2006).

Madanat et al (1997) first used random effects to account for unobserved heterogeneity in a probit model for bridge deck deterioration. Random effects were used to control for unobserved effects within observations from the same bridge. Then, Madanat and Shin (1998), within the same concept, used random effects in modeling linear pavement distress progression. Archilla (2006) identified that pavement data constitute a specific case of panel data referred to as "repeated measurements." Condition measurements taken in time at the same pavement section are typically correlated. Thus, Archilla (2006) controlled for a pavement section's unobserved effects and serial correlation in the estimation of a rutting progression model. Yu et al (2007) focused on the ability of mixed models to predict accurately the condition of specific pavement sections. Chu and Durango-Cohen (2008) empirically compared various pavement performance models and concluded that models that account for unobserved heterogeneity show improved predictive capabilities. Also, Hong and Prozzi (2010) used random coefficients to estimate a roughness progression model. They identified that mixed models can be used for both the network and project levels of pavement management because they are capable of providing "population-based" and "subpopulation-based" estimates.

### 2.1.3.2 Artificial Neural Network Analysis

Artificial neural networks (ANN) can be described as adaptive systems used to abstract the underlying relationships between dependent and independent variables and express them as weight matrices (Washington et al, 2011). ANN analysis has become extremely popular because it is convenient and often results in reliable mathematical models that emulate numerical model components (Washington et al, 2011). This is important because the pavement deterioration process is complex, and trying to find an appropriate functional form is often a difficult task. For these reasons, many researchers have used ANN for analyzing pavement performance data (Attoh-Okine, 1994; Ferregut et al, 1999; Shekharan, 2000; Lou et al, 2001; Yang et al, 2003; Miradi and Molenaar, 2007; Kargah-Ostadi et al, 2010).

Regarding the application of this type of analysis in highway agencies, Ferregut et al (1999) developed an ANN methodology for the Texas DOT using Falling Weight Deflectometer (FWD) data to estimate the remaining life of flexible pavements. Also, the Florida DOT investigated the use of ANN for forecasting short-term pavement condition and concluded that this technique gave more reliable predictions compared to traditional regression techniques (Lou et al, 2001; Yang et al, 2003). More recently, Pekcan et al (2008) developed an ANN software package to assess pavement rehabilitation strategies through FWD back-calculation for the Illinois DOT.

## 2.2 Criteria for Modeling Technique Selection

In selecting an appropriate modeling technique for rehabilitation treatment performance analysis to be incorporated into a PMS framework, a number of factors should be considered, and a discussion of them follows.

### 2.2.1 Data Characteristics and Requirements

The nature of the data is one of the most important criteria for selecting a modeling technique. Data characteristics in pavement analysis include the spatio-temporal structure of the data (time-series, cross-sectional, or panel) and the nature of the of pavement performance indicator (continuous or discrete variable). Data availability (in terms of the amount of data and the variety of relevant explanatory variables) is also of paramount importance.

### 2.2.2 Performance Prediction and Service Life Estimation

Effective pavement management requires both the prediction of pavement performance following rehabilitation treatment application and using the developed performance model and/or other considerations, in order to make a determination of the treatment effectiveness of the sustained increase in performance or the treatment service life. From a deterministic standpoint, this is often accomplished by developing treatment performance models, followed by estimation of service life. From a probabilistic standpoint, this is often accomplished by using survival functions directly.

### 2.2.3 Deterministic/Probabilistic Techniques

It has been argued that pavement deterioration and failure are stochastic phenomena that cannot be adequately explained using deterministic models (Jiang et al, 1988; Paterson, 1987). However, it should be recognized that when a purely probabilistic approach is chosen for a task at a low level of management, asset performance prediction can only be done if it is fully ensured that the subsequent management levels, such as needs assessment, project prioritization, and project programming, can be carried out effectively using probabilistic inputs. At the current time, it is not certain that this is the case in most agencies' PMSs.

### 2.2.4 Prediction Reliability

Pavement managers need reliable techniques to ascertain the effectiveness of their actions. The evaluation of the prediction reliability of modeling techniques can be performed on the basis of the theoretical background of each technique, inferences made by previous research studies, and lessons learned from practice. Thus, modeling techniques that have the greatest potential for providing reliable outcomes are preferred for use.

### 2.2.5 Network-Level and Project-Level Pavement Management

Pavement management is typically practiced at two levels: the network level and the project level (Haas et al, 1994). Some performance modeling techniques, such as Markov chain-based models (Butt et al, 1994), are more appropriately suited for an entire pavement network or a pavement family, but not a single pavement section. Similarly, certain techniques, such as autoregressive models (Prozzi and Madanat, 2003) are more appropriately suited for a single pavement section. Modeling techniques that are suited for both project level and network level predictions are preferred for use because they can allow for integration between the two management levels.

## 2.3 Selection of Modeling Technique

Using the criteria presented in Section 2.2, the empirical modeling techniques presented in Section 2.1 were evaluated on the basis of inferences made from past studies/applications and general theoretical background on these techniques. Table 2.1 presents the criteria of interest met by each empirical technique discussed in Section 2.1.

Table 2.1 Summary Results of Empirical Modeling Techniques from Past Studies/Applications and Theoretical Background (continues on the next page)

| Empirical Technique | Technique can be used for Performance Prediction | Technique can be used for Service Life Estimation | Probabilistic Technique | Technique suited for Network-Level PMS | Technique suited for Project-Level PMS | Several Applications in Highway Agencies | Data Type | Advantages for PMS application | Disadvantages for PMS application |
|---|---|---|---|---|---|---|---|---|---|
| Univariate Curve Fitting | ✓ | ✓ | | | ✓ | ✓ | Cross-sectional or time-series data, continuous performance indicator | Requires one explanatory variable | Predictions reliability can be questioned |
| Multi-variate Regression Analysis | ✓ | ✓ | | ✓ | ✓ | ✓ | Cross-sectional or time-series data, continuous performance indicator | Easy to estimate, to interpret the results, and to use (if the explanatory variables are reasonably chosen) | Requires multiple explanatory variables; in theory, it requires that all variables causing deterioration be included to give accurate predictions |
| Bayesian Regression | ✓ | ✓ | | ✓ | ✓ | | Cross-sectional or time-series data, continuous performance indicator | Constitutes a solution for agencies that face lack of field data | Requires a source of "prior" information/ knowledge along with actual performance data to improve, in theory, on regression estimates |
| Auto-Regressive Models | ✓ | | | | ✓ | | Time-series data, continuous performance indicator | Typically fit the in-sample data very well. Suitable for short-term performance prediction | Requires information on previous year's performance to predict next year's performance |
| Seemingly Unrelated Equations | ✓ | ✓ | | ✓ | ✓ | | Cross-sectional or time-series data, continuous performance indicators | Captures the correlation of the different performance indicators and thus provides a more efficient estimation than single-equation approaches | Requires multiple explanatory variables and at least two indicators of pavement performance. |

Table 2.1 Summary Results of Empirical Modeling Techniques from Past Studies/Applications and Theoretical Background (starts in the previous page)

| Empirical Technique | Technique can be used for Performance Prediction | Technique can be used for Service Life Estimation | Probabilistic Technique | Technique suited for Network-Level PMS | Technique suited for Project-Level PMS | Several Applications in Highway Agencies | Data Type | Advantages for PMS application | Disadvantages for PMS application |
|---|---|---|---|---|---|---|---|---|---|
| Markov Chains | ✓ | | ✓ | ✓ | | ✓ | Cross-sectional or time-series data, ordered discrete performance indicator. | Reliable representation of the network condition and can be integrated with network programming and budgeting | Best-suited for network-level PMS |
| Survival Analysis | | ✓ | ✓ | ✓ | | | Survival data | Flexible in terms of data requirements (parametric, non-parametric, and semi-parametric approaches available) ability to be combined with risk analysis | Agencies cannot easily interpret and use the results, project-level predictions can be acquired only by parametric survival models |
| Mixed Models | ✓ | ✓ | ✓ | ✓ | ✓ | | Panel data | Accounts for unobserved variables; offers reliable "population-wide" and in-sample predictions; flexible to accommodate complicated data structures | In-sample predictions require the estimation of the model in parallel |
| Neural Networks | ✓ | ✓ | ✓ | ✓ | ✓ | | Cross-sectional or time-series data, continuous performance indicators | Considered as a universal function approximator; can more easily model nonlinear data and complex interactions | The estimation procedure resembles a "black box" and the outcome equations may be very long and complicated |

Highway agencies have utilized univariate curve fitting obviously due to the desire for simplicity, the absence of relevant pavement data, or the lack of a manageable and updated database system. Despite its simplicity, this approach is prone to serious limitations. Deterioration is assumed to depend only on one factor, which typically is age. However, this approach is too restrictive because pavements of the same age can exhibit different deterioration rates because of other influential factors, such as traffic and climate. Even though the data used for curve fitting are typically categorized in pavement families, which reduces the variation among observations, this method sacrifices effectiveness for simplicity and cannot be considered reliable for PMS.

Regression analysis has been widely used by researchers for modeling pavement deterioration up to the 1990s. However, during the last 15 years, a widespread notion was born that regression analysis, typically, is not appropriate for pavement performance and condition data (Madanat and Shin, 1998). Even earlier, it was realized that pavement deterioration and failure are stochastic phenomena that cannot be captured by a deterministic model (Jiang et al, 1988; Paterson, 1987). Markov chain-based models have been adopted by several highway agencies; however, this method can be used as a complementary method in PMS for network-level predictions rather than an exclusive performance prediction method for an entire system. Survival models have not been widely implemented in highway agencies. The only attempt to develop survival curves was performed by the Illinois DOT, from which the basic contribution from the developed performance curves was the concept of average service lives (50% probability) for the different treatments and pavement families. Survival analysis in pavement management also can be used for network-level physical and monetary needs assessment. Ford (2011) proposed a general framework for highway agencies regarding asset life estimation using risk-based and probabilistic approaches and demonstrated the benefits of using survival analysis for asset life estimation in long-term capital needs assessment.

Other performance modeling techniques have been used to only a small extent, if any. Autoregressive models could be useful to an agency only for very short-term predictions due to the fact that the performance data of the previous time period are needed for the prediction of the next time period's performance. Also, Bayesian Regression could be used when there is a lack of field data; however, the incorporation of expert opinion into the analysis may lead to a large disparity of results (George, 2000) and is probably the reason why this technique has not been used widely. Neural network analysis is a technique that is convenient and generic, the goal of which is to predict efficiently and not to offer insight regarding a phenomenon (Karlaftis and Vlahogianni, 2011). The estimation procedure resembles a "black box," which is probably the reason why the technique has not seen wide application.

To sum up, univariate curve fitting and Markov chains have been identified as the state of practice in modeling techniques used by highway agencies. Numerous other techniques have been proposed by researchers for PMS application. Based on the review of past studies, it is concluded that mixed models constitute a promising technique for PMS application because they are suitable for panel data (typically the structure of pavement information) and can offer reliable deterministic predictions (Yu et al, 2007).

## 2.4 Review of Significant Pavement Deterioration Factors

General factors affecting pavement deterioration and service life can be categorized as pavement characteristics (e.g., age, construction/design type, predominant material, soil properties, and maintenance/rehabilitation intensities and frequencies), traffic loading characteristics (e.g., average daily traffic, truck percentage, and ESALs), and environmental characteristics (e.g., climate and weather). A review of such factors is discussed in the following subsections.

### 2.4.1 Pavement-Related Factors

Pavement-related factors have included surface type (rigid, flexible, and composite) and thickness, construction quality, structure and overlay age, bituminous asphalt type (virgin/recycled), milling depth, subgrade moisture conditions, and frequency and intensity of pavement maintenance and rehabilitation (Attoh-Okine and Roddis, 1994; Vepa et al, 1996; Baker et al, 1998; Gharaibeh and Darter, 2003; Morian et al, 2005). The quality and characteristics of aggregates, the level of bonding, the layer properties, and the degree of compaction have also been found to significantly affect bituminous asphalt deterioration (Witczak and Bell, 1978; Noureldin, 1997; Ziari and Khabiri, 2007). The quality and thickness of the pavement base material have also been identified as influential (Raad et al, 1993; Romanoschi et al, 1999).

### 2.4.2 Traffic-Related Factors

Traffic loading, particularly truck traffic, causes fatigue and leads to surface distresses and/or structural damage to the pavement. Cumulative ESALs, overweight truck loading, annual average daily traffic (AADT), and annual average truck traffic have been identified as the primary influential factors of pavement deterioration (Gharaibeh and Darter, 2003; Kumara et al, 2004; Oh et al, 2007; Irfan et al, 2009a; Khurshid et al, 2009a).

### 2.4.3 Environment-Related Factors

Environmental and climatic factors, such as temperature, temperature gradient in the asphalt, number of freeze-thaw cycles, freeze-index, precipitation, timing and duration of wet base, and subgrade conditions have been found to significantly affect pavement deterioration (Puccinelli and Jackson, 2007; Dore and Imbs, 2007; Zuo et al, 2007; Irfan et al, 2009a; Khurshid et al, 2009a). Temperature levels and variations affect the viscosity of asphalt binders, which in turn may affect the stiffness of asphalt pavements; and for a typical annual temperature variation, the stiffness of asphalt changes by more than one order of magnitude as temperature increases (HRB, 1962).

## 2.5 Chapter Summary

This chapter focused on identifying a modeling technique that could serve as a basis for a methodological framework for rehabilitation treatment analysis within a PMS. First, a literature review of the state of the practice and state of the art techniques and methods for predicting pavement deterioration and/or for estimating treatment service life was presented. The chapter identified that mixed models constitute a promising technique for pavement management. The theoretical background of mixed linear models and their applicability in PMS are discussed in Chapter 3.

# CHAPTER 3 PERFORMANCE PREDICTION METHODOLOGICAL FRAMEWORK FOR PAVEMENT MANAGEMENT SYSTEMS

As discussed in Chapter 1, a pavement management system (PMS) is a set of tools or methods that assist decision-makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time (AASHTO, 2001). Closely tied to the development of optimal strategies is the development of mathematical models that predict the future condition of a pavement on the basis of past deterioration trends. As such, pavement deterioration models constitute a major part of the set of tools deployed by pavement managers. These models are typically used to predict the condition not only of specific pavement sections, but also of the entire pavement network, and contribute to the development of long-term scheduling of rehabilitation and reconstruction as well as the determination of future funding needs for these activities. Haas et al (1994) identified the following essential characteristics of a PMS: the capability of being constantly updated, providing information about the current and future pavement condition at the network and project levels, and using feedback information for enhancing future decision-making. Therefore, the deterioration models deployed in pavement management should be able to fulfill these previously-mentioned essential features of a PMS, particularly regarding the timing of future pavement activities.

Pavement rehabilitation, one of the three major categories of pavement activities, is the focus of this thesis. In this chapter, advanced methods that account for the peculiar nature of pavement rehabilitation data to describe and predict the performance of rehabilitation treatments are described, illustrated in case studies and validated. The chapter proposes a methodological framework specifically developed for pavement management requirements and purposes.

## 3.1. The Contribution of Rehabilitation Treatment Performance Models in Providing Input Data for PMS

The use of appropriate advanced modeling techniques for predicting the performance of rehabilitation treatments may bear substantial benefits to a PMS. Increased precision in terms of predictions can reduce the uncertainty in network-level planning, programming, and budgeting. Moreover, by using more reliable models, the highway agency is placed in a better position to be more accountable to taxpayers and also to be more confident in funding requests from the legislature. The use of inappropriate approaches in rehabilitation treatment analysis could lead to inaccurate predictions, which in turn would lead to failure to estimate the actual network future needs, and ultimately in misallocation of scarce resources. Last but not least, inaccurate perception of the effectiveness of rehabilitation treatments would negatively impact future treatment selection decision-making at the project level.

Therefore, the following outcomes of rehabilitation treatment performance analysis are essential inputs for pavement management:

- Performance models unique to each rehabilitation treatment. The use of such models would assist pavement managers at the planning stage of project development in comparing alternative rehabilitation treatments and in identifying the optimal rehabilitation treatment through life-cycle cost analysis. Short-term and long-term performance predictions of in-service pavements that have received some rehabilitation are also essential for the management of the pavement network.

- Long-term treatment effectiveness models or estimates, such as the average rehabilitation treatment service life. This information can be used by pavement managers for project-level and network-level decision-making for pavement preservation. Moreover, treatment service life is a measure of treatment effectiveness, thus service life estimates can be used to evaluate the treatments based on their effectiveness or cost-effectiveness; results from treatment evaluation can enhance PMS preservation strategies, pavement design guides, and rehabilitation manuals.

In choosing a rehabilitation treatment analysis framework for PMS, the focus should be on the actual system needs; however, this does not constitute a new concept. Hajek et al (1985) suggested that pavement performance prediction within a PMS framework should serve the objectives and purposes of the PMS. As evidenced from the literature review presented in Chapter 2, the performance prediction methods deployed by agency PMSs still need significant improvement in order to produce very reliable performance estimates that are required to accomplish effective pavement management. This problem is caused partly by the challenges introduced to rehabilitation treatment analysis by the nature of pavement data, which is the focus of the next section.

## 3.2 The Characteristics of Pavement Rehabilitation Data

To conduct a rehabilitation treatment analysis, information on the post-rehabilitation pavement performance is needed. Pavement rehabilitation data extracted from a pavement management database usually refer to different rehabilitation treatments that were applied in several pavement sections at different points in time. A typical structure of this kind of data is shown in Figure 3.1.

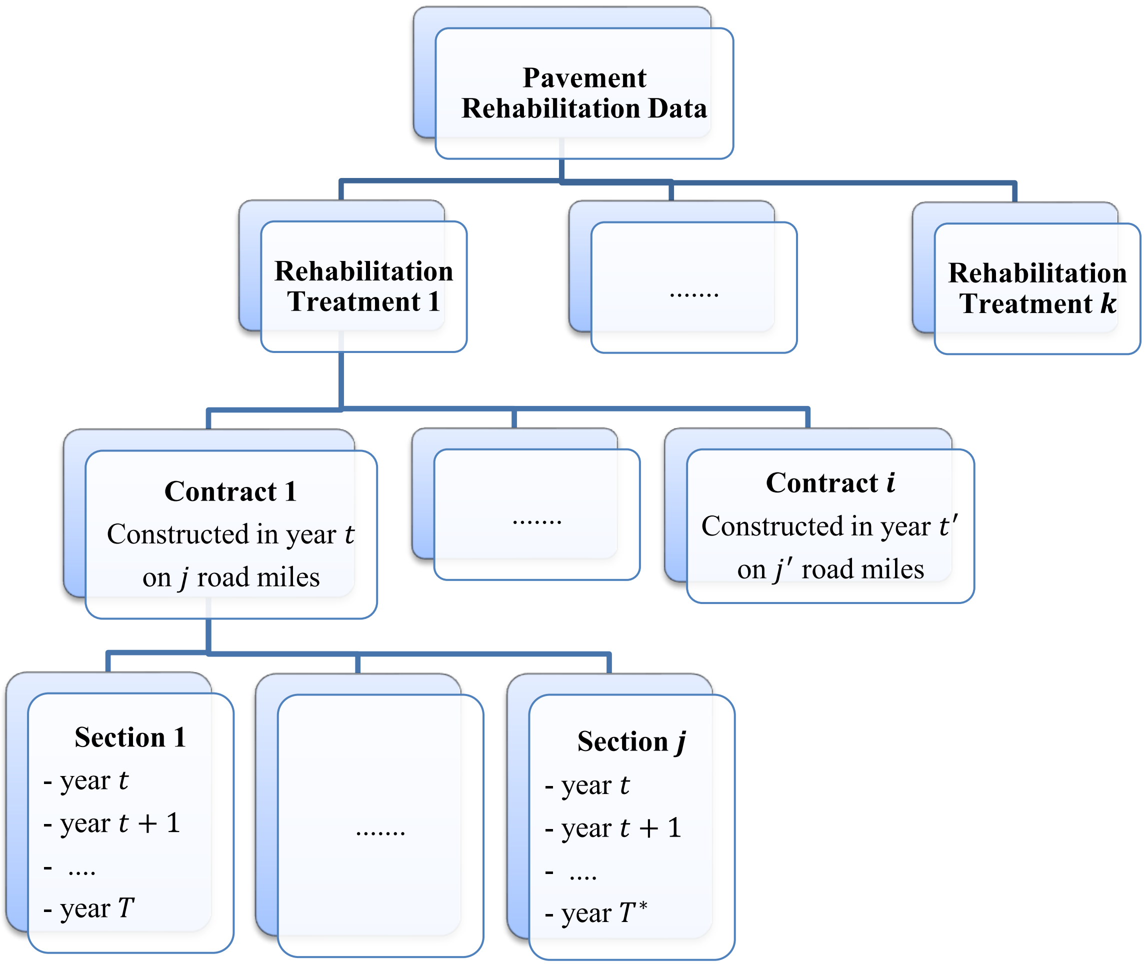


Figure 3.1 A Typical Structure of Pavement Rehabilitation Data

Pavement data for a specific treatment are typically derived from past contracts; in Figure 3.1, it is shown that data referring to Treatment 1 are from $i$ past contracts. A single rehabilitation contract typically involves the rehabilitation of several miles of pavement. To avoid information over-aggregation and the concomitant consequences, this thesis assumes that each contract consistd of multiple pavement sections. The length of each pavement section can be established by the researcher or pavement manager on the basis of data availability and practicality. Contracts of relatively small length (1-2 miles) could each be considered as one pavement section (in practice, however, this is often not the case). To this end, each longer contract section can be decomposed into 1-

mile pavement sections up to 1/10th-mile pavement sections, depending on the pattern pavement condition is monitored. It should be noted that using the smallest possible unit to define pavement sections may be neither practical nor favorable for the analysis; decomposing a contract into too many sections would result in too many observations in the dataset with the same characteristics, such as traffic and climate. Thus, in this thesis, 1-mile-long pavement sections are used for analyzing treatment performance.

For each pavement section, information on the parameters of interest, namely, performance indicators, traffic, climate, pavement type, and layer thicknesses, was collected for all years subsequent to the treatment application. This type of data structure is a combination of time-series and cross-sectional data, typically referred to as panel data (Washington et al, 2011). Pavement data constitute a special case of panel data referred to as repeated measures data because it typically consists of multiple condition measurements in time for the same observation unit (Davidian and Giltinan, 1995), in this case, the pavement section.

As demonstrated in Figure 3.1 for pavement rehabilitation data, contracts within the same rehabilitation treatment are constructed in different points in time and consist of different numbers of pavement sections: contract 1 was constructed in year $t$ over $j$ miles (which correspond to $j$ pavement sections in this case) while contract $i$ was constructed in year $t'$ over $j'$ miles. To conduct an analysis regarding the performance of Treatment 1, the available information on pavement condition (supposing data on pavement condition is available up to year $X$) would be collected for all available contracts (contracts 1 to $i$). The analysis period for a specific contract begins at the year of the treatment application and ends at the year at which the most recent condition data are available, if there has been no another rehabilitation treatment applied during this time period. For contract 1, which was constructed in year $t$, the analysis period is $(X - t)$ years; for contract $i$, which was constructed in year $t'$, the analysis period is $(X - t')$ years. Assuming that $t' > t$, there are more condition measurements over time for contract 1 compared to contract $i$. In the case where the number of repeated measurements is the same for all contracts and all pavement sections within a contract, the dataset is referred to as a balanced panel dataset (Greene, 2002). In the case of this thesis, the analysis period differs among contracts within a specific treatment, which renders the dataset unbalanced. Also, a second treatment application can be another source of imbalance; namely, within a specific contract, pavement rehabilitation contracts can include numerous pavement miles which may result in having some pavement sections rehabilitated after some years and others not rehabilitated until the year of the most recent condition data. This concept is illustrated in Figure 3.1, where it is shown that the analysis period of Section 1 ends in year $T$ whereas the analysis period of Section $j$ ends in year $T^*$. In panel data analysis, unbalance is treated as a form of missing data and affects the outcome; for this reason, modeling techniques specifically developed for unbalanced panel data should be used when analyzing data on pavement treatment performance.

It becomes clearer now that pavement rehabilitation data combine a set of characteristics that makes its analysis quite challenging. To recap this discussion this far, these characteristics are summarized below:

- Information on a specific treatment appears in the form of numerous treatment applications (contracts). Each contract is assumed to comprise multiple pavement sections; for each pavement section, multiple condition measurements are available. As such, each observation in the dataset is uniquely specified by three characteristics: the contract to which it refers, a pavement section within the given contract, and a time measurement within the given pavement section. This leads to a three-level nested structure as illustrated in Figure 3.1.

- The analysis period can differ from contract to contract or from pavement section to pavement section. This leads to an unbalanced repeated-measures data structure.

Pavement rehabilitation includes a wide variety of treatments. A rehabilitation treatment may be applicable for a specific type of pavement (e.g., thin HMA overlay is used for AC pavement rehabilitation) or for all pavement types (e.g., structural HMA overlay). Pavement engineers in public highway agencies typically combine their experience on pavement rehabilitation with information about the pavement section that is planned to be rehabilitated and the existing budgetary constraints to choose the treatment to be applied. In the best case scenario, a life-cycle cost analysis is conducted and the optimal rehabilitation strategy is defined for the life of the asset. Thus, treatment selection is a rather complicated process, which could introduce serious bias in the effort to compare the effectiveness of different treatments or to estimate the effectiveness of one treatment using information from already-applied treatments.

It is important to realize that treatments are not randomly applied to pavement sections. There is a tendency to apply structurally stronger treatments to pavements that are in poor condition or have high traffic loads and “lighter” treatments to pavements in relatively superior condition or that have lower traffic loads. In recognition of this underlying decision-making procedure in treatment selection, the following inferences can be made:

- For datasets comprising data from different treatments, a statistical comparison of treatment performance may not be easily carried out in a straight forward manner because the assumption of completely-randomized design does not hold.

- Even when data from each treatment is analyzed separately (which is the context of this thesis), treatment effectiveness comparisons should be conducted with caution because of the possibility of selectivity bias.

The problem of selectivity bias in rehabilitation treatment analysis is recognized and emphasized in this section so that pavement managers are aware that the prediction models and service life estimates coming from self-selected samples are conditional (not a representation of the population). However, selectivity bias correction is not within the scope of this thesis and will not be addressed.

### 3.3. Rationale for Using Mixed Linear Modeling in Performance Modeling for PMS

The choice of method for rehabilitation treatment analysis for PMS on the basis of the nature of pavement data, practicality, precision, and the purposes for which the results will be used, is the key to successful development of a methodology for predicting rehabilitation treatment performance. Taking into account the PMS information needs regarding rehabilitation treatment analysis (presented in Section 3.1) and the pavement rehabilitation data characteristics (presented in Section 3.2), mixed linear modeling techniques were chosen to serve as the basic building blocks of the developed methodology.

Mixed models have some advantages compared to approaches previously used in pavement management. First of all, they have the ability to incorporate the complex multi-level structure of pavement data in the analysis, account for possible unobserved characteristics among observations within the same contract or within the same pavement section (unobserved heterogeneity) and allow for serial correlation correction, which is typically needed in analyzing repeated-measures data. Second, mixed models assume that the observations in the sample are a part of a larger population. In the case of pavement rehabilitation, this is an important characteristic because it allows the use of these models to predict the performance of pavement segments that are slated for rehabilitation at some future year. Last but not least, mixed models can provide highly reliable predictions regarding the performance of in-service previously-rehabilitated pavements as well as the performance of future projects; for these purposes, they deploy two different methods, namely, *Best Linear Unbiased Prediction* and *Best Linear Unbiased Estimate*.

The previously-mentioned advantages of mixed models are herein discussed in detail and their theoretical justification is provided in the next sections.

## 3.4 Mixed Linear Model Theory

In a typical regression analysis, a phenomenon is observed multiple times in space or time and the purpose is to explain and predict it through a number of explanatory variables that are assumed to partially cause this phenomenon. A general linear model that describes this typical setup can be written in matrix form as follows (Littell et al, 2006):

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e} \tag{3.1}$$

where $\boldsymbol{Y}$ is the vector of responses (representing the phenomenon to be explained), $\boldsymbol{X}$ is the vector of explanatory variables, $\boldsymbol{\beta}$ is the fixed-effects parameter vector to be estimated and $\boldsymbol{e}$ is the unobserved vector of random errors. An important assumption of the general linear model is that the random errors are independent and identically distributed according to the normal distribution with mean 0 and variance $\sigma^2$ (Littell et al, 2006):

$$\boldsymbol{e} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{\sigma^2 I}) \tag{3.2}$$

The assumption that random errors are independent and identically distributed does not hold for all data structures. In repeated-measures data, errors that belong to the same individual (pavement section in the context of this thesis) may be correlated or may have unequal variances.

The mixed model is an extension of the general linear model to allow for random effects and correlation among responses. Random effects are random variables that represent unobserved characteristics shared within the observations of a specific group, typically referred to in the literature as unobserved heterogeneity (Washington et al, 2011). The correction for serial correlation is based on the recognition that the random errors within a specified group can be correlated; the correction imposes a structure on the actual correlations through the estimation of covariance matrix **R** (Littell et al, 2006).

### 3.4.1. General Mixed Linear Model Formulation

The general mixed linear model can be written in matrix form as follows (Henderson, 1963):

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{e} \tag{3.3}$$

$$\boldsymbol{\gamma} \sim N(\mathbf{0}, \mathbf{G}) \tag{3.4}$$

$$\boldsymbol{e} \sim N(\mathbf{0}, \mathbf{R}) \tag{3.5}$$

where $\boldsymbol{Y}$ is the vector of responses, $\boldsymbol{X}$ is the vector of explanatory variables, $\boldsymbol{\beta}$ is the fixed-effects parameter vector to be estimated, $\boldsymbol{Z}$ is a vector of constants that describe the structure related to the random effects, $\boldsymbol{\gamma}$ is the vector of random variables representing the random effects, $\boldsymbol{e}$ is the vector of random errors, $\mathbf{G}$ is the covariance matrix of the random effects $\boldsymbol{\gamma}$ and $\mathbf{R}$ is the covariance matrix of the random errors. The model is termed "mixed" to reflect the presence of both fixed effects ($\boldsymbol{\beta}$) and random effects ($\boldsymbol{\gamma}$).

A key assumption of the mixed model is that $\boldsymbol{\gamma}$ and $\boldsymbol{e}$ are not correlated (Washington et al, 2011):

$$\mathrm{COV}[\boldsymbol{\gamma}, \boldsymbol{e}] = 0 \tag{3.6}$$

Hausman's test for random effects is recommended for use in checking the validity of the assumption in Eq. 3.6 (Washington et al, 2011). If the assumption does not hold, a fixed effects model could be a more appropriate alternative. The fixed effects model accounts for unobserved heterogeneity by estimating a fixed constant for each group (observations from the same pavement section, in the context of pavement data) and allows this constant to be correlated with the random errors (Greene, 2002).

Although the fixed effects model seems to be inherently less restrictive, some characteristics of the model make it impractical and thus, inappropriate to use in a PMS. First of all, the model cannot produce parameters for explanatory variables whose values do not vary within a group (Allison, 2005). In pavement performance analysis, this would mean that the variables representing attributes constant for a specific pavement section, (e.g., climate, average traffic, pavement material characteristics, and layer thicknesses) cannot be included in the model. Moreover, the model estimates as many constants as there are units (in the context of this thesis, pavement sections) in the data; and this makes the use and storage of the model quite challenging (Allison, 2005). The combination of these extenuating characteristics render the model incapable of describing and predicting the behavior of pavement sections that are not included in the dataset used for the analysis, such as sections to be rehabilitated in the future. For these reasons, fixed effects models were not considered for use in this thesis.

### 3.4.2. Estimation Methods for Mixed Models

There are numerous methods for estimating covariance parameters in mixed models, such as generalized least squares (GLS), feasible generalized least squares (FGLS), maximum likelihood (ML) and restricted maximum likelihood (REML). GLS estimation is successful for a small number of groups and a small number of observations within a group (Baltagi, 1985); therefore, modified GLS approaches, such as FGLS, or maximum likelihood estimations are preferred (Washington et al, 2011). An important property of ML and REML methods is that they accommodate data that are missing at random (a case of unbalanced panel data), which make them more appropriate for this thesis (Rubin, 1976; Little, 1995). REML is generally preferred over ML because the random effects covariance parameters are adjusted for the degrees of freedom and are thus less biased (Allison, 2011). For these reasons, REML was chosen as the estimation method for the mixed models proposed in this thesis.

Based on the REML technique, the log-likelihood function to be maximized is as follows (Littell et al, 2006):

$$l_R(\mathbf{G}, \mathbf{R}) = -\frac{1}{2}\log|\boldsymbol{V}| - \frac{1}{2}\log\left|\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{X}\right| - \frac{1}{2}\boldsymbol{r}'\boldsymbol{V}^{-1}\boldsymbol{r} - \frac{n-p}{2}\log(2\pi) \tag{3.7}$$

where $\boldsymbol{V}$ is the variance of $\boldsymbol{Y}$ estimated as $\boldsymbol{V} = Var[\boldsymbol{Y}] = \boldsymbol{Z}\mathbf{G}\boldsymbol{Z}' + \mathbf{R}$, $\boldsymbol{r}$ is the residual vector estimated as $\boldsymbol{r} = \boldsymbol{Y} - \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{Y}$, $p$ is the rank of $\boldsymbol{X}$, and $n$ is the sample size. **G** and **R** are clearly defined in Section 3.4.1.

The statistical software used in this thesis, SAS 9.2 (The SAS Institute, 2009), minimizes the log-likelihood function (Eq. 3.7) by using a ridge-stabilized Newton-Raphson algorithm.

### 3.4.3 Prediction Methods for Mixed Models

As stated in Section 3.1, the rationale for using advanced methods for modeling pavement performance within a PMS framework is the need for accurate predictions regarding the performance of in-service pavement sections as well as the performance of future projects. Specifically, for pavement rehabilitation, pavement managers need to be aware of the condition of the rehabilitated pavement sections, the average effectiveness of a past rehabilitation treatment, and the expected effectiveness of a treatment if applied to a specific pavement section in the future. Mixed model estimation offers the ability to estimate “realized values of random variables” through a method called Best Linear Unbiased Prediction (BLUP), which was first developed by Henderson (1963) and was theoretically justified as an extension of the Gauss-Markov theorem by Harville (1976).

The basic concepts of this method and its importance on pavement performance prediction are discussed in this section.

The general linear mixed model in matrix form (Eq. 3.3) is: $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{e}$. The expected value of $\boldsymbol{Y}$ can be given as follows:

$$E[\boldsymbol{Y}] = E[\boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{e}] = \boldsymbol{X\beta} \tag{3.8}$$

since the vector of random effects, $\boldsymbol{\gamma}$, and the vector of error terms, $\boldsymbol{e}$, are normally distributed with the mean equal to zero. This expectation of $\boldsymbol{Y}$ is a population-wide average and can be called *unconditional expectation* (Littell et al, 2006).

The *conditional expectation* of $\boldsymbol{Y}$ given $\boldsymbol{\gamma}$ is as follows:

$$E[\boldsymbol{Y}|\boldsymbol{\gamma}] = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} \tag{3.9}$$

As can be seen from Eq. 3.9 the conditional expectation refers to the mean of $\boldsymbol{Y}$ specific to the random effects observed in the sample.

The concept of conditional and unconditional expectation of $\boldsymbol{Y}$ in mixed models has been investigated by many researchers, which led to the determination of estimators and predictors with the minimum mean squared error (Searle, 1971; Harville, 1988; Robinson, 1991; McLean et al, 1991). In the case of unconditional expectations, it has been shown that $\boldsymbol{k}'\widehat{\boldsymbol{\beta}}$ is the best linear unbiased estimate (BLUE) of $E(y)$ (or more appropriately, the empirical best linear unbiased estimate (EBLUE) since the covariance matrices **G** and **R** are not known), where $E(y)$ is the unconditional expectation of observation $y$, and $\boldsymbol{k}'$ is the vector of explanatory variables with respect to $y$. The best linear unbiased estimator of $\boldsymbol{\beta}$, $\widehat{\boldsymbol{\beta}}$, is given as follows (Littell et al, 2006):

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}'\widehat{\boldsymbol{V}}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\widehat{\boldsymbol{V}}^{-1} \tag{3.10}$$

where $\widehat{\boldsymbol{V}}$ is the estimated variance of $\boldsymbol{Y}$.

In the case of conditional expectations, it has been shown by Henderson (1963) that the best linear unbiased predictor (BLUP) of $E(y|\boldsymbol{\gamma})$ (or the empirical best linear unbiased predictor (EBLUP)) is as follows:

$$\boldsymbol{k}'\widehat{\boldsymbol{\beta}} + \boldsymbol{m}'\widehat{\boldsymbol{\gamma}} = \boldsymbol{k}'\widehat{\boldsymbol{\beta}} + \boldsymbol{m}'\widehat{\mathbf{G}}\boldsymbol{Z}'\widehat{\boldsymbol{V}}^{-1}(\boldsymbol{Y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}) \tag{3.11}$$

where $\boldsymbol{k}'$ and $\boldsymbol{m}'$ are the vectors of the explanatory variables and constants respectively, that describe the structure related to the random effects related to observation $y$, and $\widehat{\mathbf{G}}$ is the estimated covariance vector of the random effects.

To take into account the uncertainty in the estimation of covariance matrices **G** and **R**, several bias corrections regarding the predictions have been proposed (Littell et al, 2006). The standard error adjustment for fixed effects proposed by Kenward and Roger (1997) was chosen for this thesis based on the recommendations of Littell et al (2006).

It was shown that mixed models can offer two different kinds of predictions: conditional and unconditional. The implications of this capability are of paramount importance with regard to the application of these techniques in pavement management. As mentioned previously, regarding pavement rehabilitation, pavement managers need all of the following three pieces of information:

1. prediction of the short-term and long-term post-rehabilitation performance of in-service pavement sections,
2. average effectiveness of each rehabilitation treatment, and
3. pavement performance prediction if a given rehabilitation treatment is applied to a specific pavement section in the future.

The first necessary item above for pavement management refers to pavement sections that have been rehabilitated in the past; thus, their information is included in the treatment analysis dataset, which allows *section-specific* predictions conditional on the observed random effects ($\boldsymbol{k}'\widehat{\boldsymbol{\beta}} + \boldsymbol{m}'\widehat{\boldsymbol{\gamma}}$) to be obtained using the BLUP method. The BLUP method highly increases the accuracy of these in-sample predictions, which has been shown in pavement data analysis by Yu et al (2007) and will be illustrated in the case study in Section 3.6.

The ability to accurately predict the future performance and service life of in-service pavements directly gives pavement managers the ability to assess the future network needs for maintenance and rehabilitation activities with higher certainty and reduces risk and uncertainty in the processes of programming and budgeting. BLUPs and confidence limits can be estimated automatically during the model estimation process, which makes the procedure quick and practical.

The second necessary estimation for pavement management refers to *population-wide* treatment performance and service life expectations. In order to obtain these estimates the BLUE method should be used since there is usually no pavement section in the dataset that can be assumed to represent the "average pavement section." This method actually suggests using only the fixed effects part of the mixed model ($\boldsymbol{k}'\widehat{\boldsymbol{\beta}}$) to obtain the desired predictions. To estimate the average treatment effectiveness, sample averages can be used for the vector of the explanatory variables ($\boldsymbol{k}'$) as long as they are considered representative of the population.

Last but not least, pavement managers need to know the expected performance and service life of a treatment if selected for a new project, thereby enhancing and facilitating the decision-making process of future treatment applications. These performance and service life estimates refer to pavement sections to be rehabilitated in the future; however, information on these sections does not exist in the analysis sample and estimation thus will be based on the unconditional estimation approach. To estimate the expected performance and service life in this case, the fixed effects part of the model ($\boldsymbol{k}'\widehat{\boldsymbol{\beta}}$) will be used, while the vector of explanatory variables ($\boldsymbol{k}'$) should include the specific characteristics of the pavement to be rehabilitated in the future.

In summary, the prediction methods that involve mixed models have great potential to offer more reliable deterministic results and can accommodate the information needs of pavement management. This capability is probably the greatest advantage of incorporating a mixed model methodology in pavement management.

## 3.5 Applicability of Mixed Linear Models in PMS

In the previous sections, the theoretical background of mixed linear models was discussed. The nature of these models is such that they provide a high level of flexibility in selecting appropriate formulations to fit a specific data structure. In the following sections, the formulations that are considered appropriate, based on the characteristics of pavement rehabilitation data, are described.

### 3.5.1 The One-Way Random Effects Model

For a given pavement section, unobserved heterogeneity could represent information that was not collected but has an important effect on the deterioration process. Such information could be the thickness of different pavement layers, maintenance and rehabilitation history, quality of the contractor, and weather conditions on the day of the treatment application. Gathering data to include all these attributes is costly. Therefore, existing PMS databases typically include basic information for modeling pavement performance, such as data on pavement condition and traffic. Thus, it is important to use models that can account for unobserved factors of the pavement deterioration process. An example of such a model is the one-way random effects model.

The one-way random effects model has been extensively used for panel data analysis in pavement research. This model has been reported in literature as the random effects model or two-level hierarchical linear model (Littell et al, 2006). In general, this model assumes that there are unobserved characteristics (unobserved heterogeneity) among the observations from a given individual (pavement section in the context of this study) or among the observations from different individuals for a given time period; the intercept term of the regression model can be assumed to capture any individual or time heterogeneity included in the panel data (Hsiao, 2003). Most studies on pavement performance prediction that included the use of mixed models have used random effects to correct for individual heterogeneity bias (Madanat et al, 1997; Madanat and Shin, 1998; Yu et al, 2007; Chu and Durango-Cohen, 2008; Nakat et al, 2008; Hong and Prozzi, 2010; Aguiar-Moya et al, 2011), since observations within a given pavement section are more likely to share unobserved effects than different pavement sections at given points in time.

The formulation of the one-way random effects model for unbalanced panel data can be written as follows (Greene, 2002):

$$Y_{jt} = \boldsymbol{X_{jt}\beta} + u_j + e_{jt}, \quad j = 1, \dots, S \quad t = 1, \dots T_j \tag{3.12}$$

$$u_j \sim N(0, \sigma_u^2) \tag{3.13}$$

$$e_{jt} \sim N(0, \sigma_e^2) \tag{3.14}$$

where $j$ refers to pavement sections; $S$ is the total number of pavement sections in the sample; $t$ refers to the time periods available for the pavement section $j$; $T_j$ is the analysis period for the pavement section $j$, $Y_{jt}$ is the performance of the pavement section $j$, $t$ years after rehabilitation; $\boldsymbol{\beta}$ is the $k \times 1$ vector of parameters to be estimated; $\boldsymbol{X_{jt}}$ is the $1 \times k$ vector of the explanatory variables; $u_j$ is the unobserved heterogeneity term which is randomly distributed across individuals but constant through time for the same pavement section; and $e_{jt}$ is the random disturbance term. Both $u_j$ and $e_{jt}$ are assumed to be normally distributed with constant variances $\sigma_u^2$ and $\sigma_e^2$, respectively.

As mentioned in Section 3.4.1, a key assumption of this model is that $u_j$ is uncorrelated with the explanatory variables ($E[u_j|\mathbf{X}] = 0$); and the validity of this assumption can be checked with the Hausman's test (Washington et al, 2011).

The one-way random effects model accounts for possible unobserved heterogeneity regarding the observations within the same pavement section. However, the typical structure of pavement rehabilitation data presented in Figure 3.1 implies that a strong possibility for unobserved effects exists among the observations that belong to the same contract. As such, a more appropriate model that accounts for the structure of the pavement rehabilitation data is necessary. This is discussed in the next section.

### 3.5.2. The Three-Level Nested Linear Model

The one-way random effects model has been used by many researchers for pavement performance modeling because it can accommodate a simple panel data structure. However, data on pavement rehabilitation treatments inherently constitute a rather complicated structure (demonstrated in Figure 3.2); and the one-way random effects model therefore may be inadequate to fully describe the underlying phenomena.

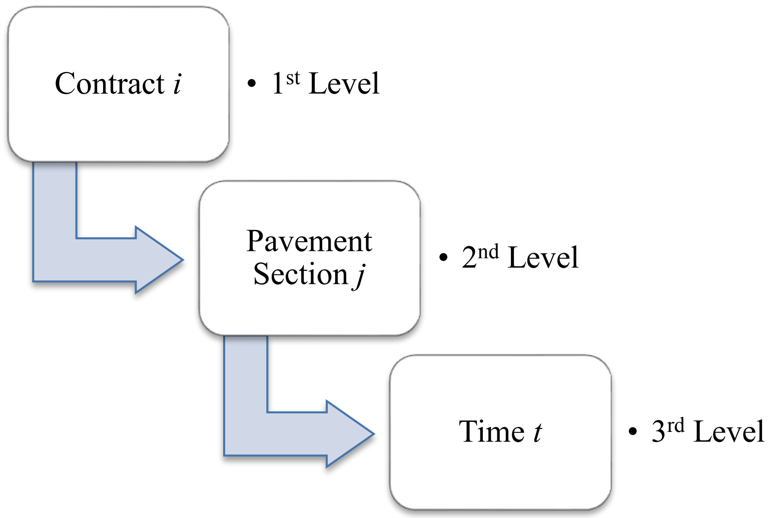


Figure 3.2 Three-level Nested Data Structure for a Specific Treatment

To analyze the performance of a rehabilitation treatment, information on past contracts must be collected. As discussed in Section 3.2, a contract typically comprises multiple pavement sections. Then, for a specific pavement section, there are multiple performance measurements over time for that pavement section. As shown in Figure 3.2, pavement section $j$ is one of the pavement sections that constitute contract $i$, and time $t$ refers to an observation in time for pavement section $j$ of contract $i$. These relationships among the observations are consistent with a three-level nested structure.

In this thesis, a mixed model is used to accommodate this nested structure because it is reasonable to postulate that unobserved characteristics exist at both the contract level and the pavement section level. Observations that belong to the same contract may share similar unobserved characteristics, such as the quality of the applied treatment, and other characteristics related to that treatment application. Thus, individual instances of treatment applications under the same treatment name may display significant differences in their outcomes. For example, the actual thickness of an overlay may differ across the overlay contracts. Small differences in the new overlay thickness can have a significant impact on future pavement condition (Bardaka and Karlaftis, 2012); however this information is rarely repeated. Regarding the observations that belong to the same pavement section, possible unobserved heterogeneity may be related to a lack of information on the pavement section layer thicknesses before the treatment, the subgrade quality, the maintenance and rehabilitation history, and the weather conditions on the day of the treatment application.

The formulation of the three-level nested linear model for unbalanced panel data can be written as follows (Littell et al, 2006):

$$Y_{ijt} = \boldsymbol{X_{ijt}\beta} + \alpha_i + u_{j(i)} + e_{t(ij)},\ \ i = 1, \dots, N \quad j = 1, \dots, S_i \quad t = 1, \dots, T_{ij} \tag{3.15}$$

$$\alpha_i \sim N(0, \sigma_a^2) \tag{3.16}$$

$$u_{j(i)} \sim N(0, \sigma_u^2) \tag{3.17}$$

$$e_{t(ij)} \sim N(0, \sigma_e^2) \tag{3.18}$$

where $i$ refers to a specific contract, $N$ is the total number of contracts in the sample, $j$ refers to a specific pavement section within contract $i$, $S_i$ is the total number of pavement sections within contract $i$, $t$ refers to a specific observation in time for section $j$, $T_{ij}$ is the total number of years of available pavement performance information for section $j$ from contract $i$, $Y_{ijt}$ is the performance of pavement section $j$ within contract $i$ $t$ years after rehabilitation, $\boldsymbol{\beta}$ is the $k \times 1$ vector of the parameters to be estimated, $\boldsymbol{X_{ijt}}$ is the $1 \times k$ vector of the explanatory variables, $\alpha_i$ is the effect of the $i^{\text{th}}$ contract, $u_{j(i)}$ is the effect of pavement section $j$ from contract $i$, and $e_{t(ij)}$ is the random error term.

Random effects and errors are assumed to be normally distributed with constant variances (Eq. 16-18). Also, zero correlation is assumed between any two measurements in time within a pavement section. This assumption may be considered too restrictive in the case of pavement data. If serial correlation exists, this assumption could be relaxed in order to represent more accurately the relationships among the observations within the same section. The next section discusses this issue.

### 3.5.3 Serial Correlation Correction in Repeated-Measures Data

Pavement monitoring in a PMS includes collection of performance information for the pavement network, often at equally-spaced points in time and, typically, every one or two years. Several years of monitoring result in datasets with multiple performance measurements on the same pavement section; these datasets are characterized by panel data termed *repeated measures* (Davidian and Giltinan, 1995). In this thesis, repeated measures appear under the second level of the data structure shown in Figure 3.2 and refer to the multiple performance observations at a given pavement section.

Most repeated measures data (as such repeated measures data at a given pavement section) are typically correlated (Davidian and Giltinan, 1995). However, the covariance structure that describes the relationships between pairs of repeated measures has not been adequately investigated in previous studies on pavement performance modeling. Most of the mixed model formulations for pavement deterioration deployed by previous studies have used the one-way random effects model presented in Section 3.5.1. This model is estimated under the assumption of the variance components structure; and the same covariance structure is assumed by the three-level nested linear model presented in Section 3.5.2. The variance components structure assumes that repeated measurements within a pavement section are not correlated and have a constant variance, and is written as follows (The SAS Institute, 2009):

$$\Sigma = \sigma^2 \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ & 1 & 0 & \cdots & 0 \\ & & 1 & \cdots & 0 \\ & & & \ddots & \vdots \\ & & & & 1 \end{bmatrix} \tag{3.19}$$

where $\sigma^2$ is the variance of the random error $e_{ijt}$, $\mathrm{Var}[e_{ijt}]$, which remains constant for any $e_{ijt}$.

This simplified covariance structure is probably the least appropriate structure for repeated measurements. Typically, two measurements in adjacent points in time tend to be more highly correlated than two observations taken in points further away in time (Ott and Longnecker, 2008). The least restrictive covariance structure that can be used in repeated measurements analysis is called an unstructured covariance model and is written as follows (Littell et al, 2006):

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1t_{\max}} \\ & \sigma_2^2 & \sigma_{23} & \cdots & \sigma_{2t_{\max}} \\ & & \sigma_3^2 & \cdots & \vdots \\ & & & \ddots & \sigma_{t_{\max-1}t_{\max}} \\ & & & & \sigma_{t_{\max}}^2 \end{bmatrix} \tag{3.20}$$

where $t_{max}$ is the maximum number of years of repeated measurements available in the sample, $\sigma_1^2$ is the variance of measurements taken one year after rehabilitation, $\sigma_{12}$ is the covariance between the measurement taken one year after rehabilitation and that taken two years after rehabilitation, and so on.

As can be seen in the covariance matrix of Eq. (3.20), every within-pavement-section error is specified to have its own variance, and every within-pavement-section pair of errors is specified to have its own covariance (Littell et al, 2006). Although this model assumes no structure for the covariance matrix and estimates the actual relationships without any restrictions, it dramatically increases the model estimation time and requires the estimation of $t_{max} \times (t_{max} + 1)/2$ parameters (this amounts to 91 parameters for a dataset with $t_{max}$ = 13). For these reasons, it is important to adopt a structured approach for the covariance matrix if serial correlation is detected and addressed.

One of the simplest covariance structures that can be used is referred to as compound symmetry (Littell et al, 2006). Under the assumption of compound symmetry, the variance-covariance matrix of the repeated measures for a pavement section is modeled as follows (Littell et al, 2006):

$$\Sigma = \sigma^2 \begin{bmatrix} 1 & \rho & \rho & \dots & \rho \\ & 1 & \rho & \dots & \rho \\ & & 1 & \dots & \rho \\ & & & \ddots & \vdots \\ & & & & 1 \end{bmatrix} \tag{3.21}$$

where $\sigma^2$ is the variance of $e_{ijt}$, $\mathrm{Var}[e_{ijt}]$, which remains constant for any $e_{ijt}$, and $\rho$ is the correlation between any two measures on the same pavement section. The covariance between any two measures on the same section, $\mathrm{Cov}[e_{ijt}, e_{ijt'}]$, is equal to $\rho\sigma^2$ and is the same for all pairs of repeated observations. Compound symmetry requires the estimation of only two parameters ($\sigma^2$ and $\rho$); however, it is not certain that it adequately describes the actual relationships among repeated measures.

The need to investigate the covariance structure of repeated performance measurements in pavement data analysis has been identified by at least one study. Archilla (2006), with rutting as the performance indicator, used the first-order autoregressive model as an appropriate covariance structure to correct for serial correlation in pavement data. The covariance matrix assumed by the first-order autoregressive model is given as follows (Littell et al, 2006):

$$\Sigma = \sigma^2 \begin{bmatrix} 1 & \rho & \rho^2 & \dots & \rho^{t_{\max}-1} \\ & 1 & \rho & \dots & \rho^{t_{\max}-2} \\ & & 1 & \dots & \vdots \\ & & & \ddots & \rho \\ & & & & 1 \end{bmatrix} \tag{3.22}$$

where $\sigma^2$ is the variance of $e_{ijt}$, $\mathrm{Var}[e_{ijt}]$, which remains constant for any $e_{ijt}$, $\rho$ is the correlation between any two adjacent errors within the same pavement section and $t_{max}$ is the maximum number of repeated measurements available in the sample. The first-order autoregressive model assumes that the correlation between any two adjacent within-section errors remains constant and equal to $\rho$. Also, the correlation between any two errors that are two points in time apart remains constant and equal to $\rho^2$. Similarly, the correlation between any two errors that are $k$ points in time apart is equal to $\rho^k$. Although this model requires the estimation of only two parameters ($\sigma^2$ and $\rho$), it assumes decreasing correlations with increasing time lags, which is a more reasonable assumption for repeated measures compared to compound symmetry.

Other possible covariance structures that could be used are the Toeplitz model and first-order ante-dependence model (a complete list of all possible structures can be found in The SAS Institute, 2009). The Toeplitz model assumes that all variances are the same and that the correlation between any two errors that are $k$ points in time apart is equal to $\rho_k$ (Littell et al, 2006):

$$\Sigma = \sigma^2 \begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{t_{\max}-1} \\ & 1 & \rho_1 & \cdots & \rho_{t_{\max}-2} \\ & & 1 & \cdots & \vdots \\ & & & \ddots & \rho_1 \\ & & & & 1 \end{bmatrix} \tag{3.23}$$

The Toeplitz model is less restrictive that the autoregressive model but requires the estimation of $t_{max}$ parameters. The first-order ante-dependence model is a more general structure that allows for unequal variances but requires the estimation of $(2 \times t_{max} - 1)$ parameters (Littell et al, 2006):

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_1 & \sigma_1\sigma_3\rho_1\rho_2 & \cdots & \sigma_1\sigma_{t_{\max}}\rho_1\rho_2\cdots\rho_{t_{\max}-1} \\ & \sigma_2^2 & \sigma_2\sigma_3\rho_2 & \cdots & \sigma_2\sigma_{t_{\max}}\rho_2\rho_3\cdots\rho_{t_{\max}-1} \\ & & \sigma_3^2 & \cdots & \vdots \\ & & & \ddots & \sigma_{t_{\max}-1}\sigma_{t_{\max}}\rho_{t_{\max}-1} \\ & & & & \sigma_{t_{\max}}^2 \end{bmatrix} \tag{3.24}$$

The question becomes how to effectively choose the appropriate structure. One solution is to repeat the analysis multiple times with different structures each time and to measure the difference in model fit with likelihood ratio tests. However, this approach requires a significant amount of effort and time. Littell et al (2006) proposed a graphical approach for identifying appropriate structures. The approach is illustrated in Section 3.6.2 as part of a case study. In general, this approach requires estimating the unstructured covariance model and plotting the estimated covariance parameters in order to identify possible covariance trends.

Using an appropriate covariance structure is crucial for the unbiased estimation of standard errors in a repeated measurements analysis (Guerin and Stroup, 2000). Surprisingly, very little research related to pavement performance modeling has been conducted in this area. One of the objectives of this thesis is to explicitly illustrate the steps that lead to choosing an appropriate covariance structure and to propose the structure that is most likely to be an accurate representation of post-rehabilitated pavement data. This will facilitate the work of pavement managers who will consider adopting the performance modeling methodology proposed by this thesis.

## 3.6. Case Study: Performance of Functional HMA Overlay Applications at Indiana Interstate Pavements

This section demonstrates the application of the approaches presented in Section 3.5 to pavement rehabilitation data collected as part of a research study conducted for the Indiana Department of Transportation (INDOT). The procedures of model formulation selection, serial correlation correction for repeated measures, estimation of predictions, and results interpretation are demonstrated in detail here. The sample used for this case study includes information on rehabilitated Interstate pavements from the Indiana road network. Information on the sample and the modeling variables is shown in Tables 3.1 and 3.2.

Table 3.1 General Sample Description

| | |
|---|---|
| Highway Asset Type: | Pavements |
| Functional Class: | Interstates |
| Rehabilitation Treatment Type: | Functional HMA Overlay |
| Performance Indicator: | International Roughness Index |
| Performance Records Availability: | 1995-2009 |
| Years of Treatment Applications: | From 1996 to 2006 |
| Total Number of Treatment Applications (Contracts): | 36 |
| Total Number of Rehabilitated Miles (Pavement Sections): | 232 |
| Total Number of Observations in the Dataset: | 1955 |
| Maximum Number of Years of Performance Records in the Dataset (Repeated Measures): | 13 |

Table 3.2. Descriptive Statistics of Available Variables

| Variable Description (*Variable Name*) | Unit | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| International Roughness Index (*IRI*) | in/mile | 73.4 | 28.6 | 11.0 | 214.0 |
| IRI Before the Treatment Application (*Pre-Treatment IRI*) | in/mile | 90.8 | 34.7 | 43.0 | 278.5 |
| Number of Years After Treatment Application (*Treatment Age*) | years | 5.1 | 3.0 | 1.0 | 13.0 |
| Average Annual Daily Traffic (*AADT*) | veh/day | 52,361 | 38,112 | 10,328 | 180,419 |
| Average Annual Daily Commercial Vehicle Traffic[a] (*Commercial Vehicles*) | veh/day | 13,648 | 7,140 | 1,630 | 43,852 |
| Freeze Index (*Freeze Index*) | degree-days | 326.6 | 186.1 | 0.0 | 721.0 |
| Annual Precipitation (*Precipitation*) | in/year | 41.1 | 3.1 | 36.6 | 48.0 |

a Commercial Vehicle Traffic includes any vehicle that belongs to Categories 4-13 reported by the FHWA Vehicle Classification Scheme F Report.

### 3.6.1. Selection of Model Formulation

This section demonstrates the process of selecting the appropriate model formulation and interpreting the results. The statistical software used in this thesis is SAS 9.2; and the code used to develop the models presented in this section is presented in Appendix A.

The starting point was to develop a linear regression model for the performance of functional HMA overlay using IRI as the performance indicator. The model is formulated as follows:

$$IRI_w = \boldsymbol{X_w \beta} + e_w, \qquad w = 1, \ldots, N \tag{3.25}$$

$$e_w \sim N(0, \sigma_e^2) \tag{3.26}$$

where $IRI_w$ is the IRI for observation $w$, $\boldsymbol{X_w}$ is the $1 \times k$ vector of explanatory variables, $\boldsymbol{\beta}$ is the $k \times 1$ vector of parameters to be estimated, $e_w$ is the error term which is assumed to be normally distributed with mean 0 and variance $\sigma_e^2$, and $N$ is the sample size.

The results of the regression model that yielded the best fit are shown in Table 3.3. The presented model was estimated with restricted maximum likelihood (REML) so that comparisons with the mixed models regarding the general fit can be easily made. OLS estimation was also performed and yielded parameter values that are consistent with those of REML.

Table 3.3. Linear Regression Parameter Estimates of the Performance of Functional HMA Overlay (Performance Indicator: IRI)

| Variable | Parameter Estimate | t-Statistic | Prob > \| t \| |
|---|---|---|---|
| Constant, $b_0$ | -186.04 | -20.43 | < 0.0001 |
| Treatment Age [years] | 3.592 | 23.35 | < 0.0001 |
| Commercial Vehicles [1000veh/day] | 0.957 | 14.23 | < 0.0001 |
| Log(Pre-Treatment IRI) | 96.19 | 29.64 | < 0.0001 |
| Precipitation [inches/year] | 1.029 | 6.86 | < 0.0001 |
| Random Error Variance, $\sigma_e^2$ | 409.03 | 31.22[a] | < 0.0001 [a] |
| Number of Observations, $N$: 1955 | | | |
| Restricted Log-Likelihood: -8,651.5 | | | |

a For the random error variance, SAS 9.2 performs a Wald Z-test.

Table 3.3 shows the parameter estimates of the regression model for the performance of the functional HMA overlay and the tests of statistical significance (t-statistic and Prob>| t |). The signs of the parameters imply that the higher are the age of the treatment, the number of commercial vehicles per day, the IRI before the treatment application, and the annual precipitation, the more deteriorated a pavement section. These results are consistent with expectation. Also, all of the estimates are statistically significant at a 99.99% confidence level.

Linear regression may not be an appropriate approach for unbalanced panel data. For this reason, previous studies on pavement performance modeling have proposed the use of the one-way random effects model. This model, which is presented in Section 3.5.1, assumes that the observations that refer to a specific pavement section might share unobserved effects. The term "unobserved effects" refers to factors that impact pavement performance after rehabilitation but have not been measured or for which there are no existing data that describe them, such as pavement layer thicknesses or weather conditions during treatment construction. The one-way random effects model was estimated with REML using the variables presented in Table 3.3 in order that comparisons of the general model fit could be made. The formulation of the one-way random effects model for this case study is as follows:

$$\begin{aligned} IRI_{jt} &= \boldsymbol{X_{jt}\beta} + u_j + e_{jt} \\ &= \beta_0 + \beta_1 \times Treatment\ Age_{jt} + \beta_2 \times Commercial\ Vehicles_{jt} + \beta_3 \times \\ &\quad Precipitation_j + \beta_4 \times Log(Pre - Treatment\ IRI)_j + u_j + e_{jt}, \end{aligned} \tag{3.27}$$

$$j = 1, \dots, 232 \quad t = 1, \dots, T_j$$

$$u_j \sim N(0, \sigma_u^2) \tag{3.28}$$

$$e_{jt} \sim N(0, \sigma_e^2) \tag{3.29}$$

As can be seen in Eq. 3.27, the fixed effects part of the model includes the constant ($\beta_0$) and four explanatory variables; it should be noted that $Precipitation$ and $Log(Pre - Treatment\ IRI)$ differ across pavement sections but not within the same pavement section. The term $u_j$ represents the characteristics of the pavement section $j$, which are constant over time but unobserved, and the term $e_{jt}$, which represents the random error of each observation.

The variance component $\sigma_u^2$ measures the variation of the possible unobserved effects among pavement sections. If there is statistically significant variation, it will mean that unobserved effects do exist and that this model formulation is more preferable than linear regression.

Table 3.4. One-way Random Effects Model Parameter Estimates of the Performance of Functional HMA Overlay (Performance Indicator: IRI)

| Variable | Parameter Estimate | t-Statistic | Prob > \| t \| |
|---|---|---|---|
| Constant, $b_0$ | -184.70 | -7.84 | < 0.0001 |
| Treatment Age [years] | 4.348 | 44.15 | < 0.0001 |
| Commercial Vehicles [1000veh/day] | 0.74 | 5.60 | < 0.0001 |
| Log(Pre-Treatment IRI) | 101.22 | 12.22 | < 0.0001 |
| Precipitation [inches/year] | 0.778 | 1.96 | 0.0515 |
| Pavement Section Variance, $\sigma_u^2$ | 312.74 | 10.07[a] | < 0.0001[a] |
| Random Error Variance, $\sigma_e^2$ | 130.63 | 29.32[a] | < 0.0001[a] |
| Number of Considered Groups: | 232 (pavement sections) | | |
| Number of Observations: | 1955 | | |
| Restricted Log-Likelihood: | -7,881.4 | | |

a For the random effects and error variance, SAS 9.2 performs a Wald Z-test.

Table 3.4 shows the parameter estimates of the one-way random effects model for the performance of the functional HMA overlay and the tests of statistical significance (t-statistic and Prob>| t |). The values of the parameters and their statistical significance display some differences with the linear regression model. Table 3.4 also shows the estimates of the two variance components and the associated statistic that tests if the variance is equal to zero. Based on the results from Table 3.4, it is concluded that individual unobserved heterogeneity exists and that random effects should be used to avoid estimation bias.

Since the model is estimated using REML, the general fit can be evaluated by a likelihood ratio test where the log-likelihood of the model is compared to the log-likelihood of a restricted model. In this case, the restricted model is the linear regression model presented in Table 3.3. The restricted model has one parameter fewer than the one-way random effects model, which implies that the $\mathrm{X}^2$ statistic is $\chi^2$ distributed with one degree of freedom. The $\mathrm{X}^2$ test statistic is estimated as follows:

$$X^2 = -2 \times (-8{,}651.5 + 7{,}881.4) = 1{,}540.2$$

For $X^2 = 1{,}540.2$, a confidence level of over 99.99% is obtained, which implies that the one-way random effects model is superior to the linear regression model.

This thesis suggests the use of the three-level nested linear model presented in Section 3.5.2 as a more appropriate formulation that can accommodate the structure of the data related to pavement rehabilitation. The formulation of the model for this case study (using the same independent variables with the previously presented models) is as follows:

$$\begin{aligned} IRI_{ijt} &= \boldsymbol{X_{ijt}\beta} + a_i + u_{j(i)} + e_{t(ji)} \\ &= \beta_0 + \beta_1 \times Treatment\ Age_{ijt} + \beta_2 \times Commercial\ Vehicles_{ijt} + \\ &\quad \beta_3 \times Precipitation_{ij} + \beta_4 \times Log(Pre - Treatment\ IRI)_{ij} + a_i + \\ &\quad u_{j(i)} + e_{t(ji)}, \end{aligned} \tag{3.30}$$

$i = 1, \dots, 36 \quad j = 1, \dots, S_i \quad t = 1, \dots, T_{ij}$

$$\alpha_i \sim N(0, \sigma_a^2) \tag{3.31}$$

$$u_{j(i)} \sim N(0, \sigma_u^2) \tag{3.32}$$

$$e_{t(ij)} \sim N(0, \sigma_e^2) \tag{3.33}$$

This formulation assumes that observations within the same contract and observations within the same pavement section that belongs to a given contract share unobserved characteristics captured by $\alpha_i$ and $u_{j(i)}$, respectively. The estimated parameters of the three-level nested linear model for the performance of the functional HMA overlay and the tests of statistical significance (t-statistic and Prob>|t|) are shown in Table 3.5.

Table 3.5. Three-Level Nested Linear Model Parameter Estimates of the Performance of Functional HMA Overlay (Performance Indicator: IRI)

| Variable | Parameter Estimate | t-Statistic | Prob > \| t \| |
|---|---|---|---|
| Constant, $b_0$ | -253.49 | -6.94 | < 0.0001 |
| Treatment Age [years] | 4.411 | 43.65 | < 0.0001 |
| Commercial Vehicles [1000veh/day] | 0.602 | 3.62 | 0.0003 |
| Log(Pre-Treatment IRI) | 125.60 | 14.79 | < 0.0001 |
| Precipitation [inches/year] | 1.365 | 1.70 | 0.0920 |
| Contract Variance, $\sigma_a^2$ | 344.96 | 3.57[a] | 0.0002[a] |
| Pavement Section Variance, $\sigma_u^2$ | 124.15 | 8.59[a] | < 0.0001[a] |
| Random Error Variance, $\sigma_e^2$ | 130.54 | 29.33[a] | < 0.0001[a] |
| Number of Considered Groups: | 36 contracts, 232 pavement sections | | |
| Number of Observations: | 1955 | | |
| Restricted Log-Likelihood: | -7,827.5 | | |

a For the random effects and errors variance, SAS 9.2 performs a Wald Z-test.

The effects of *Treatment Age*, *Pre-Treatment IRI,* and *Precipitation* on treatment performance were found to be stronger in this model compared to the one-way random effects model. There were also some changes in the statistical significance of some of the variables. The interpretation of the variance components is paramount for this model selection process. Both the contract and pavement section variances ($\sigma_a^2$ and $\sigma_u^2$) are statistically significant, which supports the initial assumption regarding the three-level nested data structure.

The high value of the contract variance parameter implies that the performance of different contracts differed significantly because of factors that were not observed. The variance at the contract level was also found to be higher than the variance at the pavement section level. Thus, the main source of variation for this sample was observed at the contract level, which implies that the one-way random effects model presented in Table 3.4 was probably not appropriate. However, the general fit of the model should also be evaluated by a likelihood ratio test. In this case, the restricted model was the one-way random effects model presented in Table 3.4. The restricted model had one parameter fewer compared to the three-level nested linear model, which implies that the

$X^2$ statistic is $\chi^2$ distributed with one degree of freedom. The estimation of the $X^2$ test statistic is as follows:

$$X^2 = -2 \times (-7{,}881.4 + 7{,}827.5) = 107.8$$

For $X^2 = 107.8$, a confidence level of over 99.99% was obtained, which implies that the three-level nested linear model was superior to the one-way random effects model.

In this section, the procedure of model formulation selection was demonstrated for one sample. It was concluded that the three-level nested linear model produced a superior fit compared to the other methodologies that were proposed by previous studies. However, generalized conclusions cannot be made one the basis of one sample; therefore, in Section 3.7, the different formulations are applied on multiple samples and inferences are made. The correction of possible serial correlation of the repeated measures data for this case study sample and the procedure of choosing an appropriate covariance structure are presented in the next section.

### 3.6.2. Covariance Structure Analysis

Repeated measures constitute a special case of panel data and refer to performance observations from multiple years at the same pavement section. The analysis of this type of data should include correction for serial correlation since the errors of repeated measures are typically correlated. To properly correct for serial correlation, there is a need to choose a suitable covariance structure that can be considered a good representation of the actual relationships between the pairs of repeated observations.

In the previous section, the three-level nested linear model presented in Table 3.5 was found to be the most appropriate formulation for describing the performance of the functional HMA overlay treatment. That model was estimated under the assumption of variance components (a different variance component was estimated for each random effect). In this section, the correlations between the repeated observations within a pavement section are explored and appropriate covariance structures are proposed. The unobserved effects at the contract level are still estimated using variance components analysis. A graphical approach proposed by Littell et al (2006) is used herein to identify appropriate covariance structures for the repeated measurements; the code used to develop the models presented in this section is presented in Appendix B.

The procedure begins by estimating the model presented in Eq. 3.30 under the assumption of unstructured covariance (Eq. 3.20). The model formulation and assumptions are as follows:

$$IRI_{ijt} = \boldsymbol{X_{ijt}\beta} + a_i + e_{t(ji)}, \quad i = 1, \dots, 36 \;\; j = 1, \dots, S_i \;\; t = 1, \dots, T_{ij} \tag{3.34}$$

$$\alpha_i \sim N(0, \sigma_a^2) \tag{3.35}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \cdots & \sigma_{1,13} \\ & \sigma_2^2 & \sigma_{23} & \cdots & \sigma_{2,13} \\ & & \sigma_3^2 & \cdots & \vdots \\ & & & \ddots & \sigma_{12,13} \\ & & & & \sigma_{13}^2 \end{bmatrix} \tag{3.36}$$

where $\Sigma$ is the covariance matrix of $\boldsymbol{Y}_{ij} = [Y_{ij1}, \dots, Y_{ij13}]$, which reflects the relationships of the repeated observations within the same pavement section, $\sigma_1^2$ is the variance of measurements taken one year after rehabilitation, $\sigma_{12}$ is the covariance between the measurements taken one and two years after rehabilitation, and so on. The effects of contract $i$ are assumed normally distributed with mean 0 and constant variance, $\sigma_a^2$, exactly as in the model formulation presented in Eq. 3.30.

The unstructured covariance model required the estimation of 91 parameters for the presented case. The estimation required significant time even though the number of iterations was restricted to five. Ultimately, the convergence criteria were not met, which did not constitute a serious problem because the results were used for diagnostic purposes only. The estimated variance and covariance parameters were plotted versus the time lag between them (Figure 3.3).

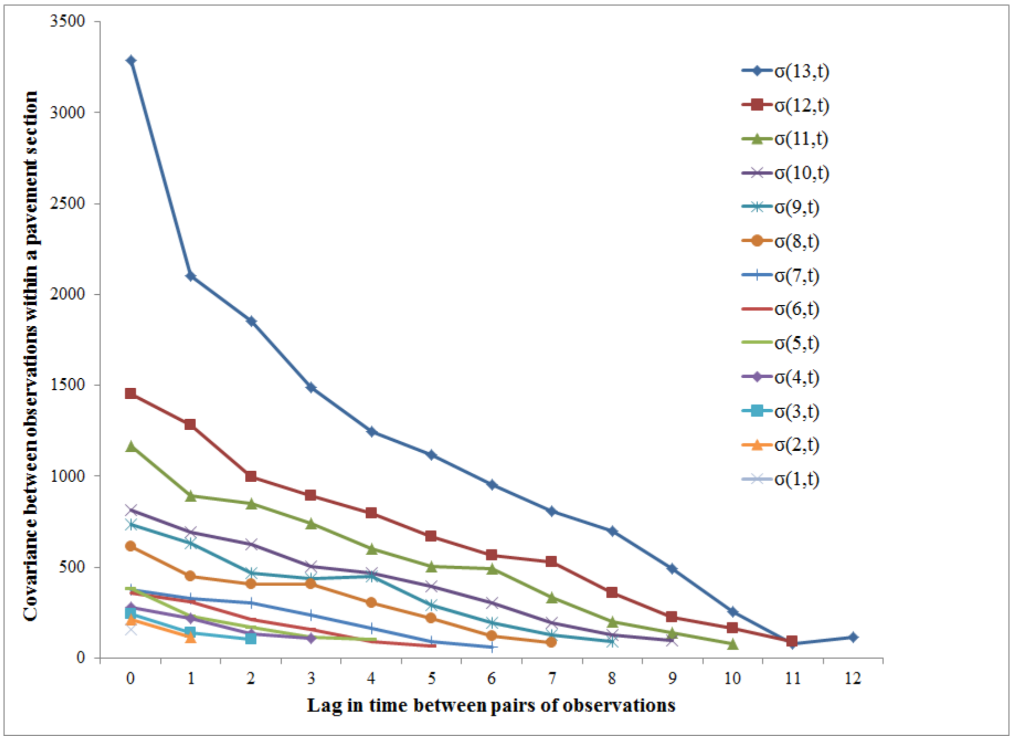


Figure 3.3 Plot of Unstructured Covariance between Repeated Observations within a Pavement Section as a Function of Lag in Time

Figure 3.3 shows the actual relationships between the repeated observations since the estimated model did not impose any structure to the covariances. The variances of the observations at each of the 13 instances correspond to the values plotted at a lag of zero. The remaining plotted values refer to the covariance values between the pairs of measurements taken in two different points in time after rehabilitation. For example, the line labeled as $\sigma(13, t)$ refers to the relationship between the observations taken 13 years after rehabilitation with the rest of the observations within a pavement section; and the value for lag equal to zero is the variance, $\sigma_{13}^2$, the value for lag equal to 1 is the covariance $\sigma_{13,12}$, and so on.

It can be observed from Figure 3.3 that, in general, a covariance decreases when the lag in time increases, which means that the covariance of two measurements taken further apart in time can be relatively smaller than the covariance of two measurements taken closer in time. As mentioned in Section 3.5.3, it is typical for repeated measures to exhibit this trend in covariance values; and for this reason, over-simpified covariance structures should be avoided. Another important feature noted in Figure 3.3 is that the variances $\sigma_1^2, \sigma_2^2, \ldots, \sigma_{13}^2$ (values for lag equal to zero) are not equal. Actually, based on the graph, higher variation can be seen among performance measurements taken many years after the treatment and smaller variation for measurements taken right after the treatment.

In summary, the two major observations from Figure 3.3 are the decreasing covariances when time lag increases and the unequal variances. An appropriate covariance structure should be able to incorporate these natural trends of the data. The first-order ante-dependence model (Eq. 3.24) may be considered an accurate representation of the actual relationships between the repeated observations, because it allows for both decreasing covariances and unequal variances[1]. The new model's formulation and assumptions are as follows:

$$IRI_{ijt} = \boldsymbol{X_{ijt}\beta} + a_i + e_{t(ji)}, \quad i = 1, \ldots, 36 \;\; j = 1, \ldots, S_i \;\; t = 1, \ldots, T_{ij} \tag{3.37}$$

$$\alpha_i \sim N(0, \sigma_a^2) \tag{3.38}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho_1 & \sigma_1\sigma_3\rho_1\rho_2 & \cdots & \sigma_1\sigma_{13}\rho_1\rho_2\cdots\rho_{12} \\ & \sigma_2^2 & \sigma_2\sigma_3\rho_2 & \cdots & \sigma_2\sigma_{13}\rho_2\rho_3\cdots\rho_{12} \\ & & \sigma_3^2 & \cdots & \vdots \\ & & & \ddots & \sigma_{12}\sigma_{13}\rho_{12} \\ & & & & \sigma_{13}^2 \end{bmatrix} \tag{3.39}$$

[1] Other structures with similar characteristics, such the Heterogeneous First Order Auto-Regressive and the Heterogeneous Compound Symmetry structures, were also tested but are not presented here because they did not lead to optimal results.

This formulation imposes a structure to the covariance matrix ($\Sigma$), which is necessary for maintaining a reasonable estimation time and avoiding the estimation of an excessive number of parameters. The next step was to estimate the model, and plot the estimated covariances as a function of the time lag in order to check the validity of the assumptions.

Table 3.6. Parameter Estimates of the Three-Level Nested Linear Model (First-Order Ante-Dependence Structure) for the Performance of Functional HMA Overlay (Performance Indicator: IRI)

| Variable | Parameter Estimate | t-Statistic | Prob > \| t \| |
|---|---|---|---|
| Constant, $b_0$ | -232.26 | -7.17 | < 0.0001 |
| Treatment Age [years] | 4.863 | 24.26 | < 0.0001 |
| Log(Pre-Treatment IRI) | 117.84 | 15.57 | < 0.0001 |
| Precipitation [inches/year] | 1.368 | 1.92 | 0.0546 |
| Contract Variance Component, $\sigma_a^2$ | 278.68 | 3.53[a] | 0.0002[a] |
| Random Error Variance on Time 1, $\sigma_1^2$ | 152.45 | 8.93[a] | < 0.0001[a] |
| Random Error Variance on Time 2, $\sigma_2^2$ | 219.61 | 8.77[a] | < 0.0001[a] |
| Random Error Variance on Time 3, $\sigma_3^2$ | 225.04 | 8.77[a] | < 0.0001[a] |
| Random Error Variance on Time 4, $\sigma_4^2$ | 253.25 | 8.74[a] | < 0.0001[a] |
| Random Error Variance on Time 5, $\sigma_5^2$ | 354.14 | 8.60[a] | < 0.0001[a] |
| Random Error Variance on Time 6, $\sigma_6^2$ | 346.61 | 7.91[a] | < 0.0001[a] |
| Random Error Variance on Time 7, $\sigma_7^2$ | 359.12 | 7.58[a] | < 0.0001[a] |
| Random Error Variance on Time 8, $\sigma_8^2$ | 547.16 | 6.79[a] | < 0.0001[a] |
| Random Error Variance on Time 9, $\sigma_9^2$ | 586.63 | 6.30[a] | < 0.0001[a] |
| Random Error Variance on Time 10, $\sigma_{10}^2$ | 718.41 | 5.91[a] | < 0.0001[a] |
| Random Error Variance on Time 11, $\sigma_{11}^2$ | 827.53 | 5.11[a] | < 0.0001[a] |
| Random Error Variance on Time 12, $\sigma_{12}^2$ | 779.65 | 4.73[a] | < 0.0001[a] |
| Random Error Variance on Time 13, $\sigma_{13}^2$ | 996.45 | 4.69[a] | < 0.0001[a] |
| Number of Considered Groups: | 36 contracts, 232 pavement sections | | |
| Number of Observations: | 1955 | | |
| Restricted Log-Likelihood: | -7,388.3 | | |

a For the random effects and errors variance, SAS 9.2 does not perform a t-test, but rather a Wald Z-test.

Table 3.6 shows the parameter estimates of the three-level nested linear model for the performance of the functional HMA overlay, under the assumption of a first-order ante-dependence structure, and the tests of statistical significance (t-statistic and Prob>|t|).

First, the $Commercial\ Vehicles$ variable, which includes the average daily traffic of any vehicle that belongs to categories 4-13 reported by the FHWA Vehicle Classification Scheme F Report, was removed from the analysis because it was found to be not statistically significant. However, the presence of heavy trucks on the roadway typically accelerates pavement deterioration so if there were data available on the number of heavy trucks only or ESALs, the result could possibly be different. Moreover, it is not surprising to see variables that are statistically significant for one model become statistically insignificant when a more appropriately specified model is used. Regarding the remaining fixed parameters, the effect of treatment age on pavement deterioration was estimated 10.3% higher compared to the model shown in Table 3.5, while the effect of pre-treatment condition and precipitation did not change significantly.

Unobserved heterogeneity shared by observations within the same contract was still estimated using random effects; and the variance component related to the unobserved contract effects, $\sigma_a^2$, was found to be statistically significant, which verified the initial assumption for unobserved effects. Table 3.6 shows the variance of each of the repeated measures. The random error variance on time 1, $\sigma_1^2$, refers to the variance of pavement performance (represented by IRI in this case) one year after the rehabilitation; and the remaining presented random errors variances can be similarly explained. It can be seen that the higher the number of years after rehabilitation the higher the variance. This result implies that during the initial years after rehabilitation, pavement performance varies less among pavement sections while there is much higher variation in performance among sections several years after rehabilitation. It can be also noted that the statistical significance of the error variances decreases with time after rehabilitation, possibly because there are a great deal more observations for the first years after the treatment application compared to the available observations for later years.

Figure 3.4 shows the estimated covariance values between the repeated observations, as a function of the lag in time. Comparing Figure 3.3 (unstructured covariance) with Figure 3.4 (first-order ante-dependence), it can be seen that the two figures share significant similarities. Thus, it can be concluded that the chosen imposed covariance structure successfully captures the observed trend of the actual covariance values.

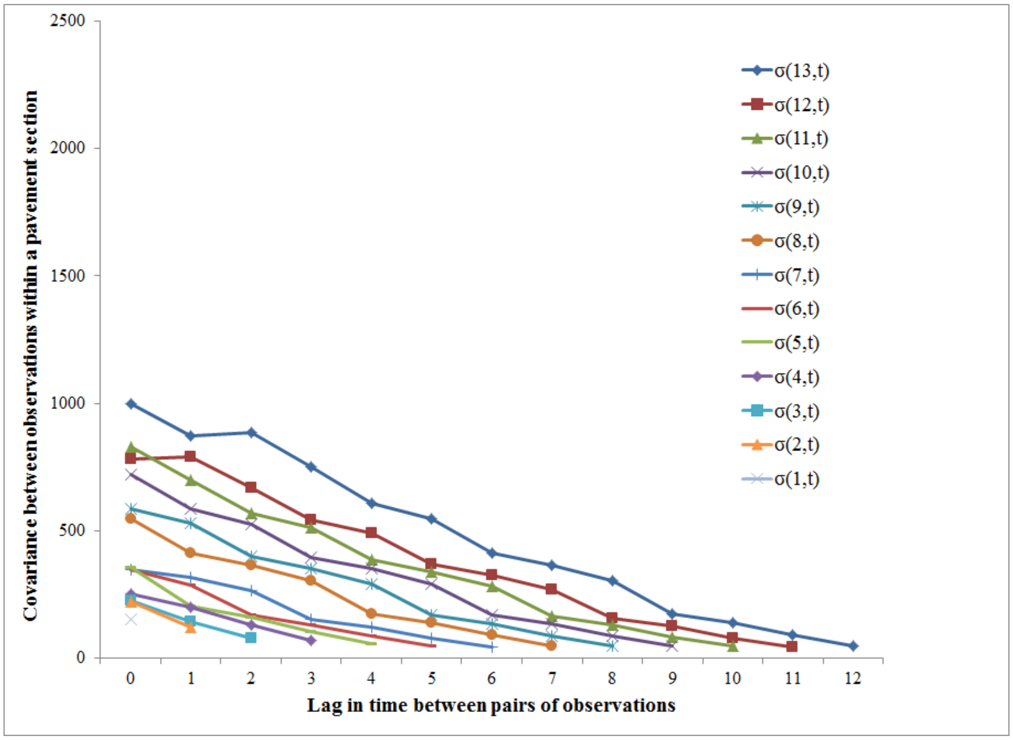


Figure 3.4 Plot of Covariance between Repeated Observations within a Pavement Section as a Function of Lag in Time (First-Order Ante-Dependence Structure)

Last but not least, the general fit of the model can be evaluated using a likelihood ratio test[2]. In this case, the restricted model is the three-level nested linear model presented in Table 3.5. The restricted model has 23 parameters fewer compared to the model presented in Table 3.6, which implies that the $\mathrm{X}^2$ statistic is $\chi^2$ distributed with 23 degrees of freedom. The estimation of the $\mathrm{X}^2$ test statistic is as follows:

$$\mathrm{X}^2 = -2 \times (-7{,}827.5 + 7{,}388.3) = 878.4$$

[2] Likelihood ratio tests cannot be conducted when the two models do not have the same number of fixed parameters. However, in this case, the removal of *Commercial Vehicles* did not significantly affect the REML of the model presented in Table 3.6.

For $X^2 = 878.4$, a confidence level of over 99.99% was obtained, which suggests that the three-level nested linear model with first-order ante-dependence covariance structure is superior to the three-level nested linear model (estimated under the variance components assumption).

In this section, the procedure of serial correlation correction was demonstrated using post-rehabilitation data from Indiana Interstate pavements. It was shown that the actual relationships between repeated measurements within a pavement section display trends and characteristics that cannot be addressed using simple structures (note that the random effects models estimated in Section 3.6.2 assumed zero correlations between pairs of repeated measurements). Thus, there is a need to identify an appropriate structure to avoid biased results. In Section 3.7, the methodology is applied to multiple samples in an effort to make more generalized conclusions about the covariance structure that can represent the typical structure and characteristics of pavement rehabilitation data, including its repeated-measure features.

### 3.6.3. Mean Performance Predictions and Service Life Estimates

The idea of investigating advanced performance modeling techniques stems from the need for unbiased pavement performance estimators in order to achieve effective pavement management. As mentioned in Section 3.4.3, mixed models present the opportunity for making two types of performance predictions: mean (population-wide) and conditional to a specific pavement section. This section focuses on the first prediction type and demonstrates how to acquire mean performance predictions and service life estimates.

Mean performance predictions can be used in pavement management to predict treatment performance for pavement sections that are planned for rehabilitation in the future; data from these sections thus have not been part of the model estimation process. These predictions can be called "population-wide" because they refer to the entire pavement network of a state or a region and not to the specific sections that were included in the analysis. In order to acquire mean predictions, only the fixed part of a mixed model is used. The previous section revealed that the three-level nested linear model with the correction for serial correlation fitted the data best, and was therefore used for making predictions. The fixed part of the model can be written as follows:

$$IRI = -232.26 + (4.863 \times Treatment\ Age) + (1.368 \times Precipitation) + \\ +(117.84 \times Log(Pre - Treatment\ IRI)) \tag{3.40}$$

It can be seen that this equation can be used exactly as a regression equation. The difference is that these parameters are unbiased because they come from an estimation procedure that takes into account the special nature of the pavement rehabilitation data. Eq. 3.40 can be used to acquire performance predictions for a pavement that will be rehabilitated in the future using a functional HMA overlay. For example, suppose that an INDOT pavement manager seeks to identify which treatment to apply on a specific Interstate pavement section and would like to know how the functional HMA overlay would perform. In this case, the specific characteristics of the Interstate would be simply substituted into Eq. 3.40. Suppose that the precipitation in the area is 40.24 in/year, the IRI before rehabilitation is 118 in/mile, and the pavement manager is interested in predicting the performance 15 years after the treatment application. This can be estimated as follows:

$$IRI = -232.26 + (4.863 \times 15) + (1.368 \times 40.24) + \big(117.84 \times Log(118)\big) \\ = 140.88\ in/mile$$

This point estimate along with confidence limits can be easily obtained automatically. For this, a code is presented in Appendix C. For this point estimate, the 95% confidence limits were 131.82 in/mile (lower limit) and 147.94 in/mile (upper limit).

Another important use of the fixed part of mixed models regarding pavement rehabilitation performance is the estimation of average treatment service life. Treatment service life can be defined as the time period between treatment application and the point when pavement performance reaches a pre-specified threshold that indicates the need for another application of the same or different treatment (Labi et al, 2005). A point estimate of the average service life of the functional HMA overlay can be estimated by using population average values for the independent variables and a threshold value for IRI, as follows:

$$IRI_{Threshold} = -232.26 + (4.863 \times Service\ Life) + (1.368 \times Precipitation) + (117.84 \times Log(Pre-Treatment\ IRI)) \quad (3.41)$$

As can be seen in Eq. 3.41, inverse prediction is necessary in order to obtain a service life estimate. This implies that confidence intervals for service life cannot be obtained because a statistical method for obtaining confidence intervals for estimates coming from inversing a multivariate linear model has not been developed (Kutner et al, 2005). However, it is not incorrect to obtain estimates and confidence limits of the average pavement performance at different treatment ages (the SAS code is presented in Appendix C) and then to plot them in order to establish boundary values for service life, as shown in Table 3.7 and Figure 3.5.

Table 3.7 Average Pavement Performance Estimates and 95% Confidence Limits with regard to Treatment Age based on Eq. 3.40

| Treatment Age | Average[a] IRI | | |
|---|---|---|---|
| | Estimate | 95% Lower Limit | 95% Upper Limit |
| 12 | 109.8 | 102.6 | 117.0 |
| 13 | 114.7 | 107.2 | 122.1 |
| 14 | 119.5 | 111.9 | 127.2 |
| 15 | 124.4 | 116.5 | 132.3 |
| 16 | 129.3 | 121.0 | 137.5 |
| 17 | 134.1 | 125.7 | 142.6 |
| 18 | 139.0 | 130.2 | 147.8 |

a Estimated using the sample average values for Precipitation and Pre-Treatment IRI

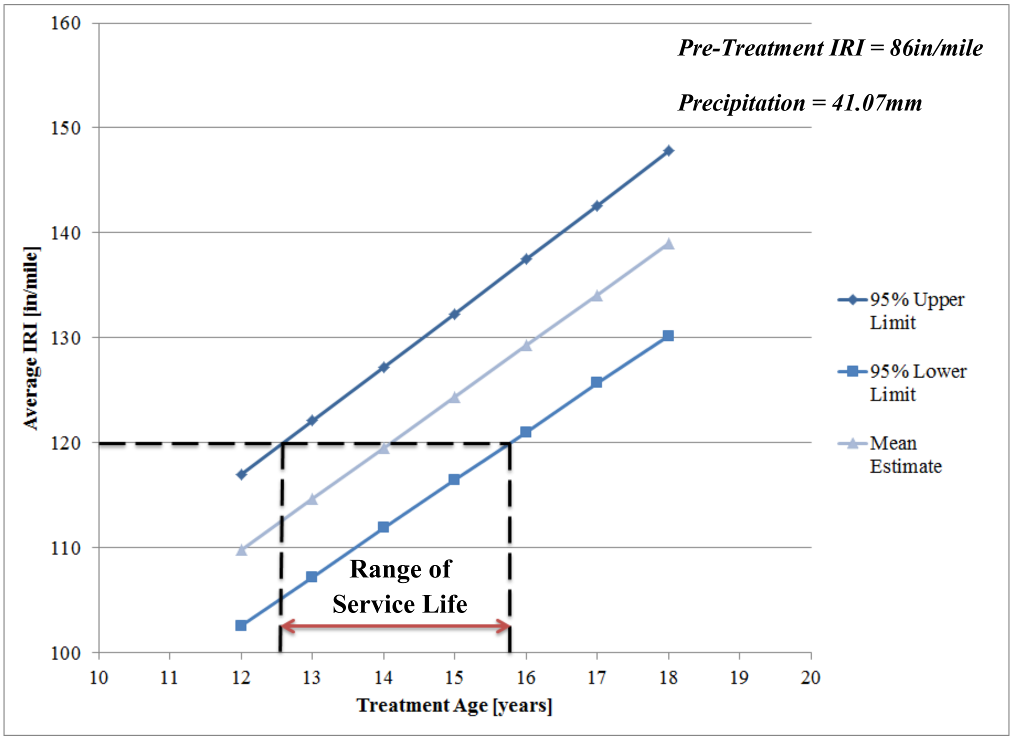


Figure 3.5 Graphical Method for Determining the Range of Functional HMA Overlay Service Life

Figure 3.5 shows a graphical technique to obtain information on the range of treatment service life. Thus, regarding the service life of functional HMA overlay on Interstate pavements, the following three things can be concluded:

- The average service life of the treatment is 14.2 years, if an IRI of 120 in/mile is assumed as the performance threshold.

- There is 95% certainty that, after 12.6 years after the treatment application, the average treatment performance will be equal to or higher than the performance threshold. This implies that, on average, treatment service life can be as low as 12.6 years.

- There is 95% certainty that, 15.8 years after the treatment application, the average treatment performance will be lower or equal to the performance threshold. This implies that, on average, treatment service life can be as high as 15.8 years.

In summary, it was found, based on 95% confidence limits for pavement performance, that the average service life of the functional HMA overlay for Interstate pavements is between 12.6 and 15.8 years, with an average of 14.2 years.

It should be noted that service life highly depends on the pre-specified performance threshold. For example, if the performance threshold for IRI is assumed to be 130 in/mile, the average service life will be equal to 16 years.

Although pavement managers would probably claim that a threshold of 120 in/mile is low, this threshold was chosen for two reasons. First, pavement performance data are aggregated per mile; thus, an average IRI of 120 in/mile for a one-mile section may mean a much higher IRI exists for smaller segments inside this section. Second, and most importantly, the fact that there are typically a great deal more observations that refer to the early ages of rehabilitation treatments (observations with relatively low IRI values) reduces the ability of models to accurately predict high IRI values, as shown in Figure 3.6.

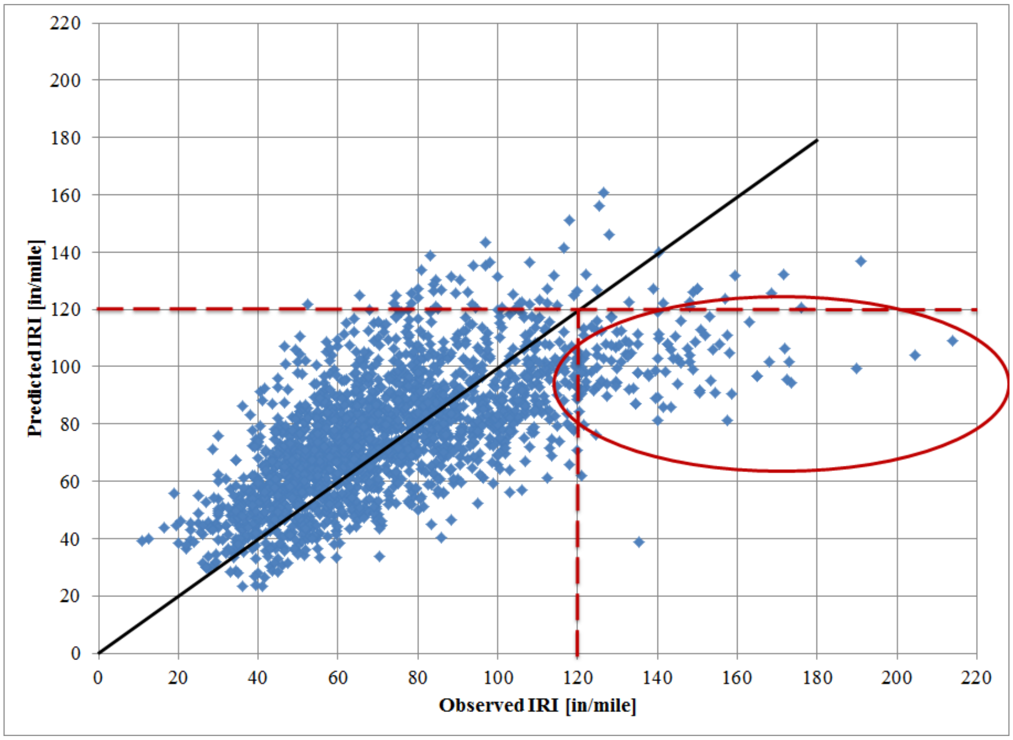


Figure 3.6 Comparison between Observed and Predicted IRI for the Three-Level Nested Linear Model with First-Order Ante-Dependence Covariance Structure (Table 3.6)

Figure 3.6 is a plot of the observed (actual) IRI values from the sample used for this case study versus the population-wide predictions acquired by the model presented in Table 3.6. The figure shows that most pavement sections observed to have actual IRI values higher than 120 in/mile are predicted to have IRI values lower than 120 in/mile (values inside the circled area). Thus, the performance threshold regarding the average service life estimates is chosen mainly based on data availability on the later ages of the treatment and should be adjusted in the future when additional measurements become available.

3.6.4. Performance Predictions for Past-Rehabilitated In-Service Pavements

In the previous section, the estimation procedure and the usefulness of population-wide predictions in pavement management were demonstrated using the functional HMA overlay treatment data from Indiana Interstate pavements. This section demonstrates the concept and the use of performance predictions conditional on a pavement section which can be obtained by using the BLUP method (Section 3.4.3).

Best Linear Unbiased Prediction (BLUP) is a method specifically developed for mixed models that can be used to estimate the “realized values of random variables” for the individuals (i.e., the contracts and pavement sections for this thesis) included in the analysis dataset. The model used in the previous section for the population-wide predictions, used serial correlation correction for the repeated measures at the pavement section level. However, the BLUP method, as proposed by Henderson (1963) and employed by the statistical software available in the market, has not been modified to be able to incorporate correction for serial correlation. The theoretical background for this correction is available. If the mixed model is corrected for serial correlation, then the BLUP forecast would be the estimate of the conditional mean plus a serial correlation factor (Frees, 2004). This corrected BLUP forecast has not been incorporated in statistical software yet and therefore must be done manually at this time. Therefore, it would be unreasonable to attempt a manual correction in this thesis because the scope is to propose a methodology that can be applicable to PMS. Thus, there is a need to identify which of the developed models is more appropriate to use for obtaining in-sample performance predictions.

The models that will be compared are the three-level nested linear model (results in Table 3.5), which uses random effects at the contract and pavement section levels, and the three-level nested linear model with a first-order ante-dependence covariance structure (results in Table 3.6), which uses random effects only at the contract level. In order to compare the two models, the conditional performance predictions on the pavement sections included in the analysis (BLUPs), which are estimated automatically during the model estimation procedure in SAS, were plotted versus the observed performance (Figures 3.7 and 3.8).

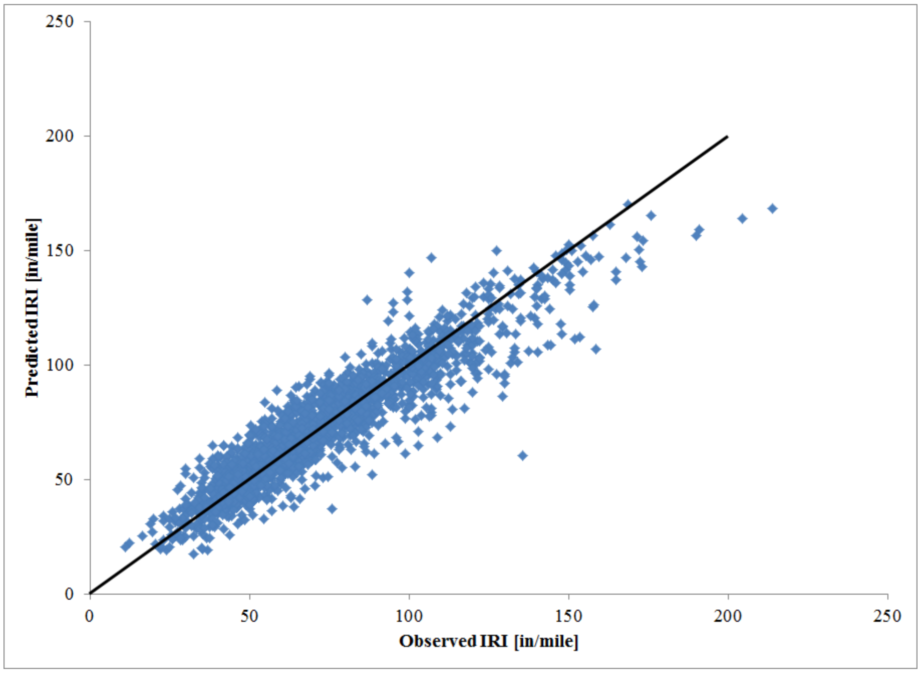


Figure 3.7 Comparison between Observed and Predicted IRI with the Method of Best Linear Unbiased Prediction for the Three-Level Nested Linear Model (Table 3.5)

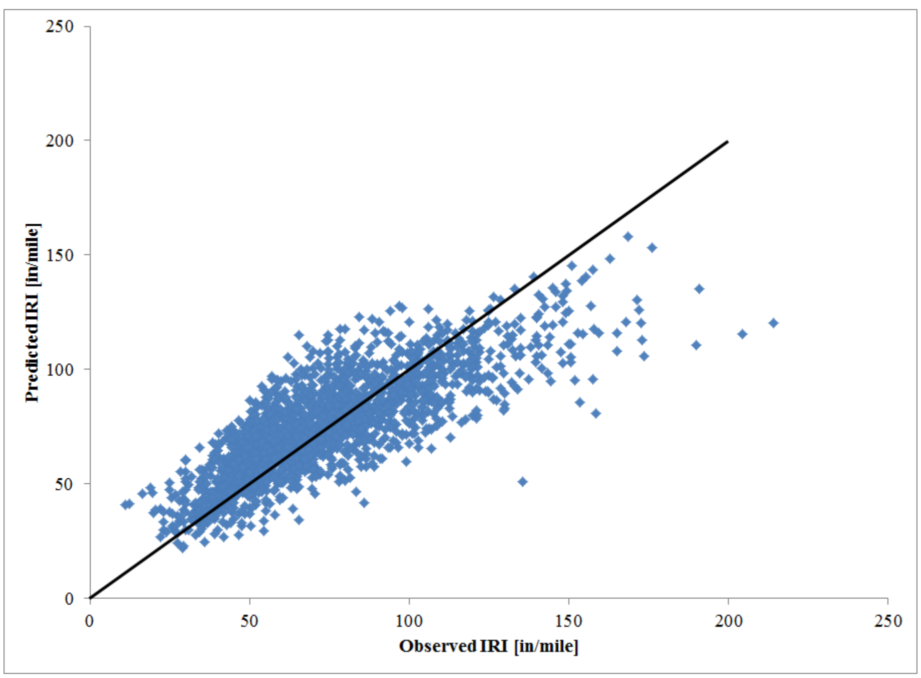


Figure 3.8 Comparison between Observed and Predicted IRI with the Method of Best Linear Unbiased Prediction for the Three-Level Nested Linear Model with First-Order Ante-Dependence Covariance Structure (Table 3.6)

When Figure 3.7 is compared to Figure 3.8, it becomes clear that the predictions obtained from the model that uses random effects both at the contract and the pavement section levels (Figure 3.7) were much closer to the observed performance values. This result was expected because the BLUP method incorporates the "realized" values of random effects into the prediction process; therefore, if a part of the variation is not explained by simple random effects (without serial correlation correction), it cannot be incorporated, and as a result the conditional predictions are not very accurate.

To understand the meaning and usefulness of section-specific performance predictions, some examples follow based on the sample used for this case study. Table 3.8 compares the roughness predictions for one pavement section (Interstate 74, miles 4-5) from the analysis sample, which were obtained using linear regression and the three-level nested linear model (for this, the SAS code is presented in Appendix C).

Table 3.8 Comparison between Linear Regression Predictions and BLUPs from the Three-Level Nested Linear Model for Interstate-74, Miles 4-5, Rehabilitated in 2001

| Treatment | Pavement Performance After Rehabilitation, represented by IRI [in/mile] | | |
|---|---|---|---|
| Age | Observed | Linear Regression[a] | 3-Level Nested Linear Model[b] |
| 5 | 48 | 81 | 53 |
| 6 | 57 | 85 | 57 |
| 7 | 50 | 89 | 62 |
| 8 | 58 | 91 | 66 |
| 9 | 62 | 95 | 70 |
| 10 | - | 98 | 74 |
| 11 | - | 102 | 79 |
| 12 | - | 105 | 83 |
| 13 | - | 109 | 88 |
| 14 | - | 112 | 92 |
| 15 | - | 116 | 96 |

a Predictions are obtained by using the model presented in Table 3.3
b Predictions are obtained using the BLUP method on the model presented in Table 3.5

Linear regression does not have the capability of producing conditional predictions, which makes the results not practical in pavement management. On the other hand, the predictions obtained from the mixed model are related to the observed roughness measurements through the BLUP method and are therefore more accurate.

Pavement managers need to be aware of the condition of rehabilitated assets so that they can effectively program future rehabilitation activities. The inability to reliably predict the need for future activities regarding in-service previously-rehabilitated pavements may lead to underestimation or overestimation of budgetary needs. For example, for the Interstate pavements that had received functional HMA overlay treatments during the years 1996 to 2006, the time of future treatment re-application was estimated as shown in Figure 3.9.

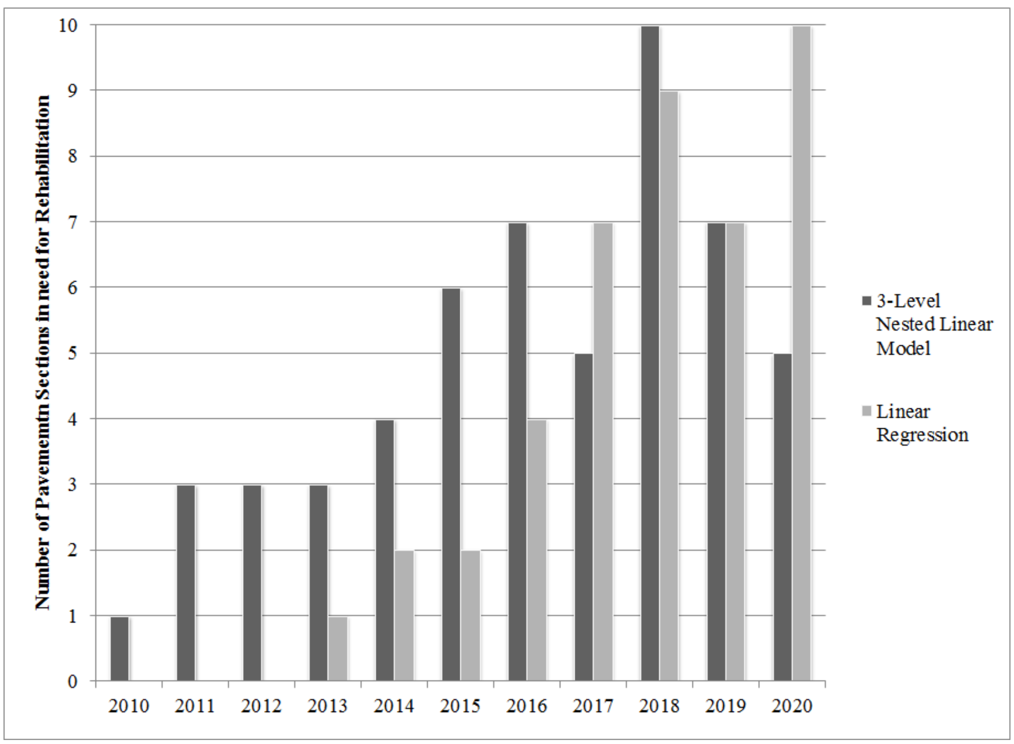


Figure 3.9 Need for Future Rehabilitation Activities of Indiana Interstate Pavement Sections in which Functional HMA Overlay had been Applied (Last Available Performance Records: 2009)

It can be seen in Figure 3.9 that simplified approaches, such as linear regression, can produce a misleading picture of a network’s needs. Specifically, linear regression predicted that most sections will need to be rehabilitated after 2017, and that a minimal number should be rehabilitated before 2015. For this reason, the use of mixed models in pavement management is highly encouraged and could lead to substantial benefits. The possible benefits of the mixed model methodology for network level needs assessment are investigated in Chapter 4.

### 3.6.5 Summary of Results

In this case study, data from Indiana Interstate pavements that had been rehabilitated with functional HMA overlay were used for demonstrating rehabilitation treatment analysis using mixed models. Specifically, the process of selecting the appropriate modeling formulation was presented and resulted in the selection of the three-level nested linear model. Then, the correction of serial correlation was illustrated and an appropriate covariance structure was chosen. Last but not least, the two types of performance predictions (population-wide and conditional) and their usage were demonstrated in detail. This case study serves as a demonstration of the discussed mixed models estimation procedures and not as a means to make inferences on the methodology. The following sections focus on making inferences and propose a methodology for pavement rehabilitation analysis.

## 3.7 Validation of Mixed Linear Modeling Formulations

In order to be able to make sound comparisons among the different approaches, there is a need for a larger-scale application. In this section, the techniques initially presented in Section 3.5 are applied to Indiana Interstate pavement data that refer to the rehabilitation treatments shown in Table 3.9.

Table 3.9 Characteristics of Available Data on Indiana Interstate Rehabilitation for Testing of Modeling Techniques.

| Rehabilitation Treatment | Total Number of Treatment Applications (Contracts) | Total Number of Rehabilitated Miles (Pavement Sections) | Total Number of Observations in the dataset |
|---|---|---|---|
| Preventive Maintenance (Thin HMA Overlay) | 10 | 89 | 621 |
| Structural HMA Overlay (Multiple Structural Layers) | 5 | 40 | 354 |
| Functional HMA Overlay[a] (Mill Surface and HMA Overlay) | 36 | 232 | 1955 |
| Crack and Seat PCC and HMA Overlay | 2 | 6 | 65 |
| Repair PCC and HMA Overlay | 12 | 72 | 694 |
| Rubblize PCC/Composite and HMA Overlay | 4 | 41 | 330 |
| PCC Overlay on PCCP | 2 | 8 | 98 |

a The data related to this treatment have been used for the case study

As can be seen in Table 3.9, information was collected for seven rehabilitation treatments that were applied to Indiana Interstate road segments in the period 1996-2006. The information available for some of these treatments was very limited, but knowing this fact will be of assistance in revealing possible restrictions of the different statistical formulations under investigation.

First, it was investigated whether there was a need to model the three-level data structure that was shown in Figure 3.2. To determine if such a need exists to take into account this structure, two statistical tests were considered. The first was a test of the statistical significance of the variance estimates of the unobserved effects at the contract and pavement section levels. If both estimates were statistically significant, it could be implied that the three-level nested linear model should be used. If only one of the variance estimates was statistically significant, it would mean that there was no need to model the three-level structure and that the one-way random effects model was sufficient. The results of the variance components test of statistical significance were combined with the results from a likelihood ratio test, which examines if there is an improvement in the general fit of a model in order to make a decision about the most appropriate formulation to be adopted. Both tests were demonstrated in Section 3.6.1 of the case study.

This procedure was followed for all available rehabilitation treatment samples (Table 3.9) and the results are shown in Table 3.10.

Table 3.10 Modeling Formulation Choice for the Available Rehabilitation Treatment Datasets

| Rehabilitation Treatment | Linear Regression | One-Way Random Effects | Three-Level Nested Linear Model |
|---|---|---|---|
| Preventive Maintenance (Thin HMA Overlay) | | | x |
| Structural HMA Overlay (Multiple Structural Layers) | | | x |
| Functional HMA Overlay (Mill Surface and HMA Overlay) | | | x |
| Crack and Seat PCC, and HMA Overlay | x | | |
| Repair PCC and HMA Overlay | | | x |
| Rubblize PCC/Composite and HMA Overlay | | x | |
| PCC Overlay on PCCP | | x | |

The following inferences can be made from Table 3.10:

- The three-level nested structure was found to be unnecessary for modeling the treatment datasets that contained information on less than four contracts. It is therefore reasonable to assume, in general, that the rehabilitation data structure should be taken into account unless the number of treatment applications (contracts) is too small (less than five) to allow any variation among the applications to be captured.

- For the data regarding Rubblized PCC/Composite and HMA Overlay and PCCP on PCC Pavement, the one-way random effects model was found to be superior to linear regression since the variation among different pavement sections was statistically significant.

- For one treatment's dataset (Crack and Seat and HMA Overlay), it was found that it is not necessary to consider any kind of unobserved effects, and linear regression therefore was considered appropriate. This result can be attributed to the limited amount of data for that treatment (i.e., the smallest dataset containing a total of 65 observations).

As a next step, it was investigated in which datasets there was a need to correct for serial correlation of the error terms of the repeated measurements within a pavement section, and which covariance structure was more appropriate. The procedure that needed to be followed for this investigation was demonstrated in detail in the case study in Section 3.6.2. Table 3.11 presents the chosen covariance structures as a result of the serial correlation correction for each sample.

Table 3.11 Covariance Structure Choice for the Within-Pavement-Section Error Terms

| Rehabilitation Treatment | First-Order Autoregressive Structure | First-Order Ante-Dependence Structure |
|---|---|---|
| Preventive Maintenance (Thin HMA Overlay) | | x |
| Structural HMA Overlay (Multiple Structural Layers) | | x |
| Functional HMA Overlay (Mill Surface and HMA Overlay) | | x |
| Repair PCC and HMA Overlay | | x |
| Rubblize PCC/Composite and HMA Overlay | x | |
| PCC Overlay on PCCP | x | |

Table 3.11 includes only two covariance structures; however, several others were tested. The first-order autoregressive structure was found to be more suitable for the datasets that lacked a sufficient number of treatment applications and/or observations. For the datasets that did not suffer from limited information, the first-order ante-dependence structure was found to be more appropriate. This change in structure choice because of the sample size was undertaken because the first-order ante-dependence structure required the estimation of ~ 20 more parameters compared to the first-order autoregressive structure. The number of parameters estimated in a model determines the sample size appropriateness (Tanaka, 1987); but there is no exact answer to the question of which sample size is considered appropriate for estimating a specific number of parameters, because it typically depends on the data. Based on the results from the datasets used in this thesis, the first-order ante-dependence structure should not be used for samples with less than ~ 500 observations.

## 3.8. Proposed Methodological Framework of Rehabilitation Treatment Analysis for PMS

Figure 3.10 presents the methodological framework proposed by this thesis for analyzing data on pavement rehabilitation treatment performance. For the purposes of illustration and ease of comprehension, the procedure is presented for observations from a single pavement family and a single rehabilitation treatment, which can be repeated for multiple families and treatments. The presented framework is designed to serve as a further improvement of the existing methods used for treatment performance prediction in highway agencies and also to serve as a catalyst for integrating project level and network level management.

It is also proposed that the presented methodology should not replace but rather complement the network-level probabilistic approaches in pavement management, such as the use of Markov chains or risk-based survival analysis for network-level physical and monetary needs assessment. This recommendation is made because the developed framework can provide reliable information regarding which of the specific assets will be in need of preservation at each future year, rather than general information only about the network performance and overall magnitude of future needs. The proposed framework consists of the following steps:

Step 1. Data Collection

The first step is to collect the data required for the analysis. The considerations at this step are as follows: (i) data from individual pavement sections that comprise each rehabilitation contract, which are the observed post-rehabilitation performance measurements at each pavement section; and (ii) selection of performance indicator(s)[3] that adequately represent pavement performance or deterioration, which are purposely selected to capture the healing effect of the treatment. These indicators include IRI, rutting, PCR, and cracking. Clearly, there is no point in selecting a performance indicator that is not affected by the rehabilitation treatment; and (iii) collection of data on the factors of pavement deterioration, including traffic, climate, and pavement-related factors (presented in detail in Section 2.4).

[3] This methodology was developed for using one performance indicator for modeling rehabilitation treatment performance. The analysis can be repeated for obtaining models for other performance indicators for the same treatment. However, previous research has proposed the use of seemingly unrelated equations for such a case (Prozzi and Hong, 2006; Anastasopoulos et al, 2012).

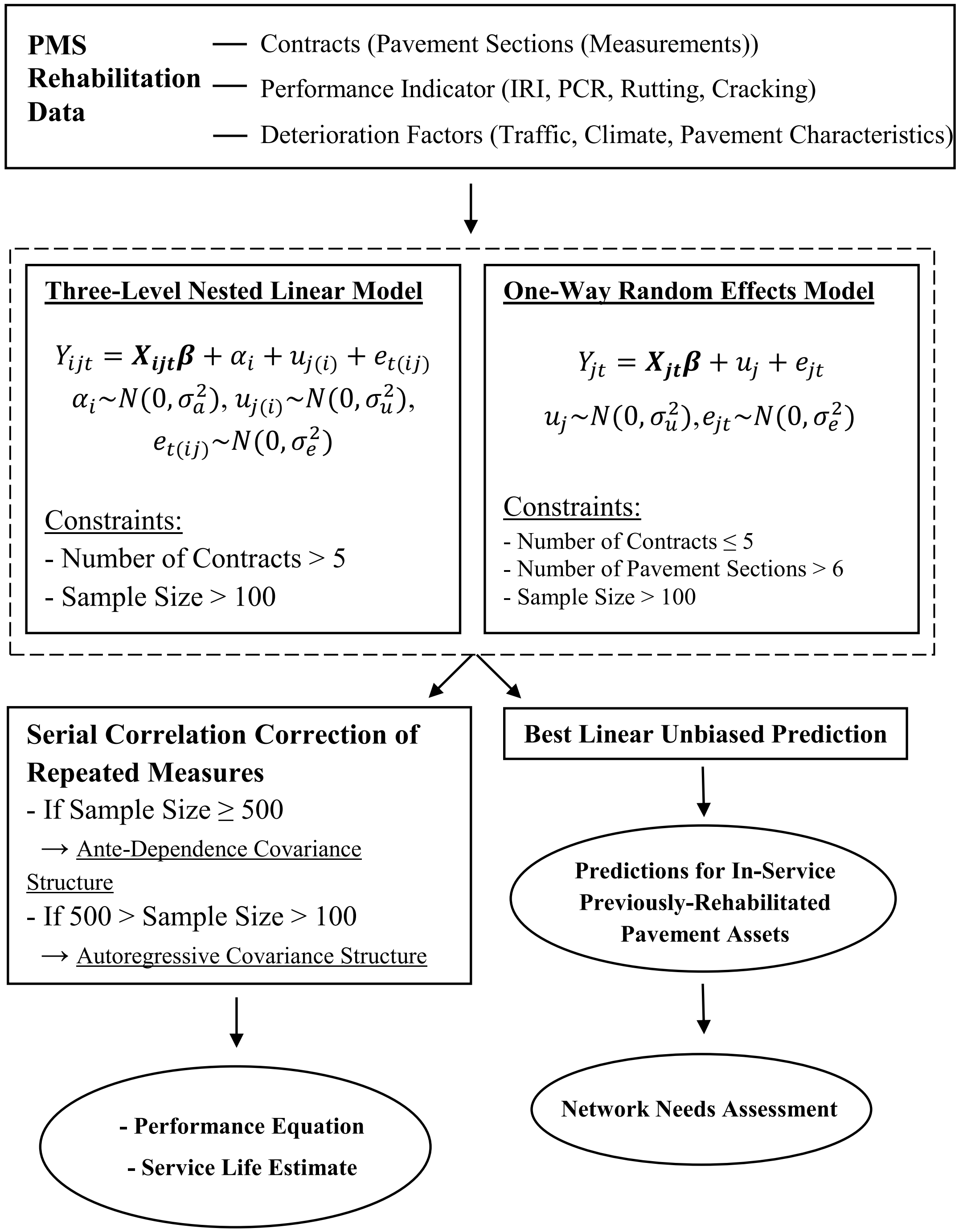


Figure 3.10 Methodological Framework of Rehabilitation Treatment Performance Prediction for PMS (Constraints and Sample Size Limitations Based on the Datasets used for Validation in Section 3.7)

Step 2. Mixed Model Formulation

In this step, the pavement performance, in terms of the selected performance indicator, is modeled as a function of the explanatory variables. The model formulation is selected on the basis of a number of sample-related constraints, which emerged from the validation of the proposed methodology (Section 3.7). If there is an adequate number of contracts in the sample (more than five), the three-level nested linear formulation is proposed; otherwise, the one-way random effects model can be used.

Step 3. Serial Correlation Correction

After deciding on the mixed model formulation, correction for serial correlation is carried out. The correction imposes a covariance structure on the repeated-measures data. The covariance structure is selected on the basis of a single constraint that is related to the sample size.

Step 4. Treatment Performance Prediction

(a) Treatment Performance Equation and Service Life Estimates

The fixed part of the model estimated in Step 3 (performance equation) is used for predicting the treatment performance for pavement assets that will receive rehabilitation at a future year and for treatment service life estimates. The procedure for this is presented in Section 3.6.3.

(b) Best Linear Unbiased Prediction (BLUP)

The BLUP method is used to obtain in-sample performance predictions (predictions for in-service previously rehabilitated pavement assets, which are included in the analysis sample). These predictions are based on the model estimated in Step 2, and the justification for this is provided in Section 3.6.4.

Step 5. Network Needs Assessment

This step analyzes the network physical and monetary needs with regard to the previously-rehabilitated pavements using the pavement section-specific predictions obtained from using the BLUP method in Step 4, as inputs. This analysis is presented in Chapter 4.

## 3.9 Limitations of Proposed Methodology

The limitations of the framework proposed in Section 3.8 are herein discussed:

### 3.9.1 Nature of the Performance Indicator

The methodology is developed for performance indicators that are continuous variables. This is not a serious limitation for pavement management because most measures of pavement performance (e.g., IRI, rutting, cracking, and friction) are continuous variables. Also, pavement condition indexes with 0-100 scale, such as PCR, are modeled as continuous. However, the methodology is not appropriate for ordered discrete performance indicators, such as the Present Serviceability Index (PSI).

### 3.9.2 Form of Deterioration Function

For relating the pavement deterioration indicator to the explanatory variables, the models presented in this chapter assume that the relationship function is intrinsically linear. In other words, the function is either linear or is a non-linear function that can be easily transformed into a linear function. The latter includes non-linear functions that are amenable to Box-Cox transformations (such as $\log_e Y$, $1/Y$, $\sqrt{Y}$, etc). For example, if the performance trends suggest the use of an exponential function, the natural logarithm of the performance indicator, $\log_e Y$, is used as the dependent variable. Also, intrinsically-linear functions include polynomials, where the indices of the variable are not in unity but can be transformed into linear functions using new variables; for example, $Y = W^2+Z^{0.5}$ becomes $Y = X_1 +X_2$, where $X_1 = W^2$ and $X_2 = Z^{0.5}$. For other types of nonlinearity, a different theoretical background is implied and linearization may be difficult; for such types, it is difficult to analyze them using the presented methodology.

### 3.9.3 Data Availability

As discussed in Section 3.7, the selection of the mixed model formulation and covariance structure type is strongly dependent on data availability. Therefore, as more information regarding treatment applications becomes available, a simplified version of the framework presented in Figure 3.10 can be used (Figure 3.11).

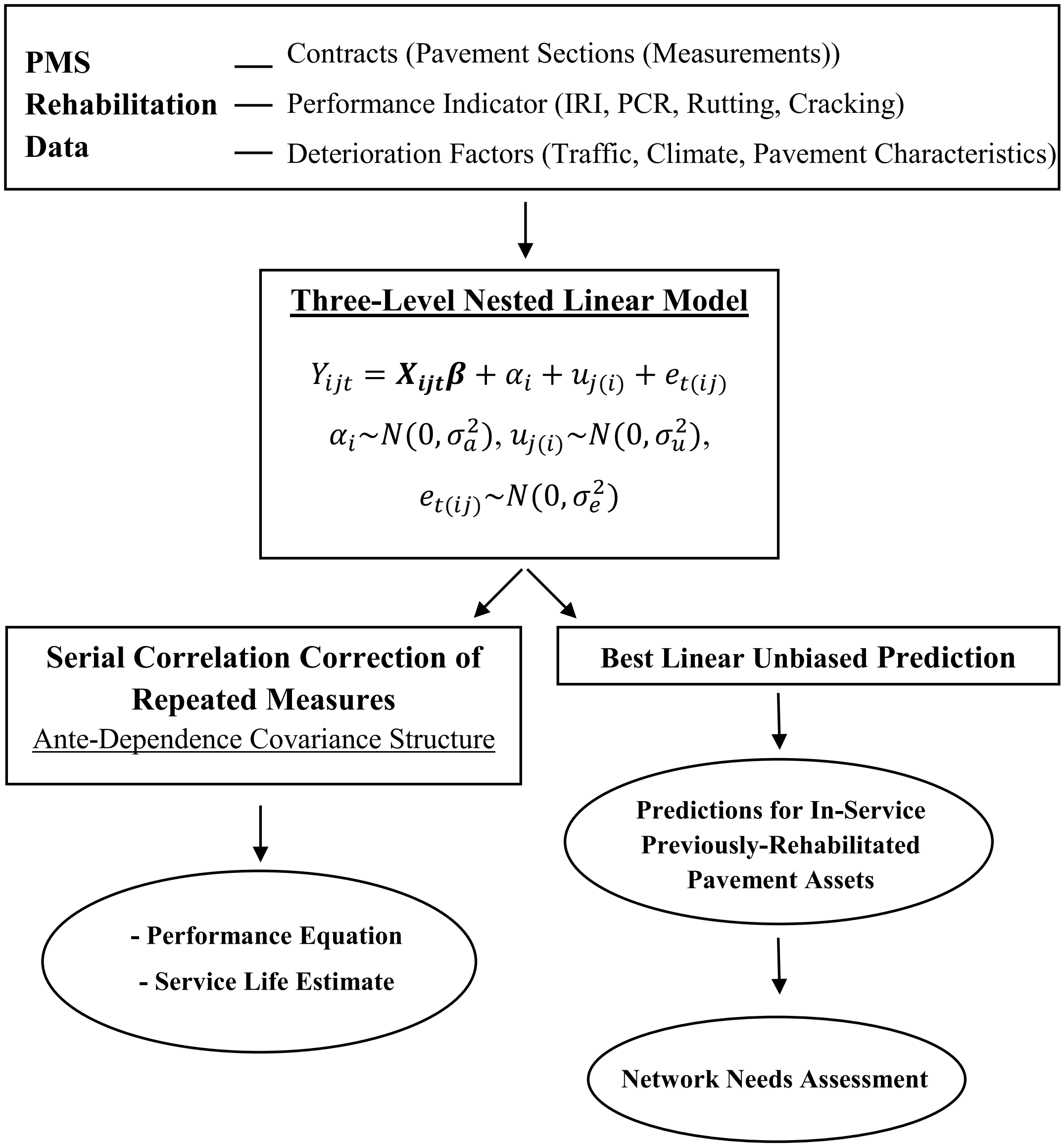


Figure 3.11 Methodological Framework of Rehabilitation Treatment Performance Prediction for PMS Assuming Full Availability of Data

3.9.4 Statistical Software Limitations

As discussed in Section 3.6.4, the modification of the BLUP method, which adds a serial correlation correction factor in the conditional predictions, has not yet been incorporated in statistical software. When the new software versions with the modified

BLUP method become available, the framework presented in Figure 3.10 should be modified, as shown in Figure 3.12.

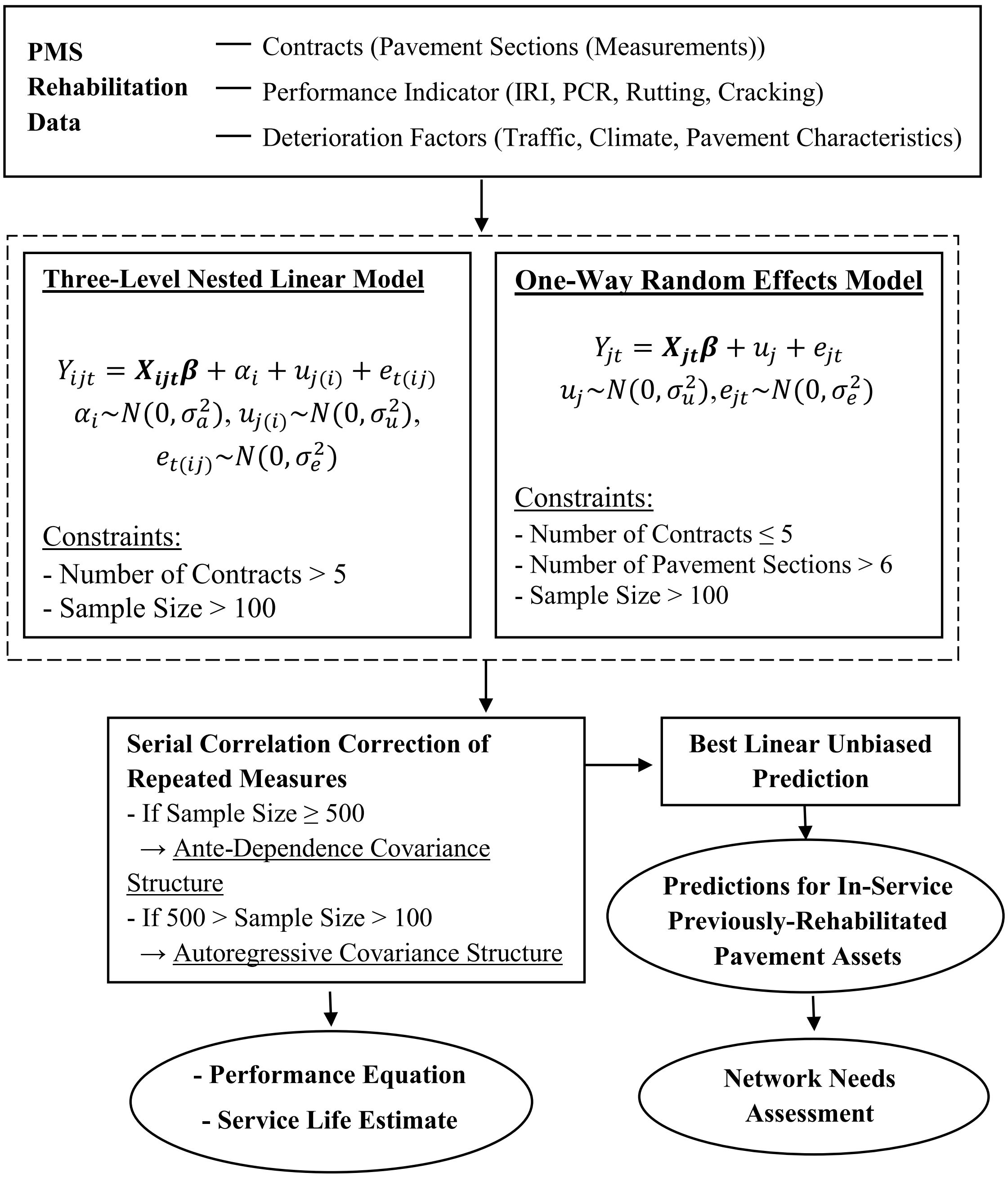


Figure 3.12 Methodological Framework of Rehabilitation Treatment Performance Prediction for PMS Assuming No Software Limitations (Constraints and Sample Size Limitations Based on the Datasets used for Validation in Section 3.7)

## 3.10 Chapter Summary

A methodological framework for pavement rehabilitation treatment analysis developed specifically for pavement management requirements and purposes, taking into cognizance the unique spatio-temporal nature of pavement rehabilitation and condition data, was presented in this chapter.

The peculiar nature of pavement rehabilitation data was first described. It was shown that information on a specific treatment appears in the form of a three-level nested structure: contracts (first level), pavement sections (second level), and performance measurements (third level). Then, the rationale for using mixed models in performance modeling for PMS was discussed. The theory of mixed linear models was presented with a focus on the general formulation of the models, the available estimation approaches, and the prediction methods and their importance to pavement management.

Regarding the applicability of mixed linear models in PMS, two formulations were identified as relevant: (1) the one-way random effects model, and (2) the three-level nested linear model. The necessity for serial correlation correction in repeated-measures pavement data was then discussed and numerous covariance structures were presented and described in detail. A case study was used to demonstrate analytically the procedure for selecting a mixed model formulation, the analysis of covariance structure, and two methodologies for obtaining predictions.

Using multiple samples from different rehabilitation treatments, it was concluded that the three-level nested linear model with a first-order ante-dependence covariance structure is most appropriate for analyzing data on pavement rehabilitation treatment performance under the following conditions: the sample has more than ~500 observations in total and the data comes from more than ~5 contracts. The proposed methodological framework was presented in Section 3.8, and its limitations were discussed in Section 3.9. The next chapter presents the impacts of using the proposed framework for the estimation of future network-level rehabilitation needs.

# CHAPTER 4 IMPACTS OF PROPOSED PERFORMANCE PREDICTION FRAMEWORK ON FUTURE REHABILITATION NEEDS ESTIMATION

Pavement management is a systematic process for maintaining the condition of pavement assets at an optimal level of service. When the network-level and project-level management, which comprise this systematic process, are integrated and occur in a coordinated framework, the system can achieve optimal holistic management. In an integrated system, a change in one of the system components will have an impact on the other system components. Thus, a methodological framework regarding a system component for incorporation in a PMS framework should not be proposed without evaluating the possible impacts to the other system components to ensure that the methodology is beneficial for the overall system. For this reason, this chapter analyzes the impacts of the proposed performance prediction framework on future rehabilitation needs assessment.

In Chapter 3, a framework for rehabilitation treatment performance prediction was proposed for incorporation in a pavement management set of tools and techniques. It was also shown that the developed methodology successfully accommodates the pavement rehabilitation data structure in the estimation procedure, thus avoiding significant estimation bias and enabling it to produce more reliable performance predictions. This chapter investigates the impacts of the proposed methodology on future rehabilitation needs assessment which is one of the key outputs of PMS. Specifically, the study investigates whether the performance predictions produced using the proposed methodology – because of their greater accuracy – can reduce the uncertainty involved in carrying out age-based and performance-based needs assessment analyses.

## 4.1 PMS Preservation Needs Assessment

Pavement preservation is a general term that typically refers to the maintenance and rehabilitation activities that are applied to pavement assets in order to maintain them at the desired level of service. Pavement managers seek to give answers to four questions regarding future preservation activities: (i) which assets are in need for preservation, (ii) which treatment is the most suitable to be applied, (iii) what is the preservation cost, and (iv) when should preservation take place (Sinha and Labi, 2012). Assessing the future preservation needs for the entire pavement network is not an easy task for pavement managers and requires information about the network inventory, the preservation cost, the preservation history of the assets, and other aspects depending on the approach chosen for determining the network physical and monetary needs.

Sinha and Labi (2013) identified three alternative methods for assessing the preservation needs of an asset network on the basis of: (i) historical spending, (ii) preservation treatment service lives, and (iii) asset performance. Assessing the network needs based on historical spending is the simplest method that can be applied and requires the least amount of information. However, this method does not take into account possible changes in the network inventory, performance standards, and preservation strategies, and may produce biased results if the time span of historical spending does not adequately represent the past trends (Labi et al, 2006). Because of the limitations of the historical trend-based needs assessment approach, the approach is not suggested for application in a PMS (Sinha and Labi, 2012).

Another possible method utilizes the average service lives of various treatments for assessing the future preservation needs, which assumes that all assets will exhibit the same performance behavior after a treatment application. This approach, which is described as the age-based needs assessment method, can be considered superior to the historical trends method, but is also prone to serious limitations (Sinha and Labi, 2012). Post-rehabilitation performance depends on several exogenous factors as well as unknown factors, as shown in Chapter 3. On the other hand, not all highway agencies can incorporate computationally-demanding approaches in their operations at the current time. As such, the age-based approach can be used successfully if the treatment service lives are reliably estimated; and this approach will be further discussed in Section 4.2. The extent to which higher accuracy in treatment service lives estimates can reduce the uncertainty in determining future preservation needs will also be discussed.

Assessing network-level needs based on the future performance of each asset is probably the most computationally intensive but most reliable approach of the needs assessment approaches (Sinha and Labi, 2012). This proposed methodology for asset performance prediction is expected to increase the reliability of the performance-based needs assessment method. In Section 4.3, this proposed performance prediction methodology's impact on predicting future physical and monetary preservation needs is investigated.

## 4.2 Impact of Treatment Service Life Estimation Method on the Age-Based Approach for Needs Assessment

Preservation needs assessment at the network level can be accomplished under the assumption that each pavement asset should be preserved after a certain time period; and that time period would correspond to the service life of the most recent preservation treatment that was applied to the asset. As such, this age-based approach assumes that there is negligible variability in post-treatment performance among the pavement assets and uses estimates of treatment service lives to define when the need for preservation will arise for each asset (Sinha and Labi, 2012). Because of this assumption, this approach may not be very reliable; however, it remains probably the best option for highway agencies that face difficulties in deploying a performance-based method. It can be hypothesized that increased accuracy in the estimation of treatment service life has a direct and positive effect on the reliability of network preservation needs estimation. This hypothesis is investigated in this section using the data from Indiana Interstates that were used in Section 3.7 to test the proposed methodology for pavement performance prediction.

Figure 4.1 presents the general framework of the age-based approach. The first step is to define a horizon period, based on the agency's long-range plan (Sinha and Labi, 2012). At the next step, the remaining service life of each pavement asset is defined by combining inventory information on the pavement assets that comprise the network (what the last preservation treatment was and when it was applied) with the service life estimates of preservation treatments. In this way, the physical needs for each pavement unit (when there is a need to preserve the asset and which treatment should be used) are established. Finally, cost models are used to estimate the cost of the needed activities and are applied to the physical needs estimations in order to determine the monetary needs for each year of the horizon period.

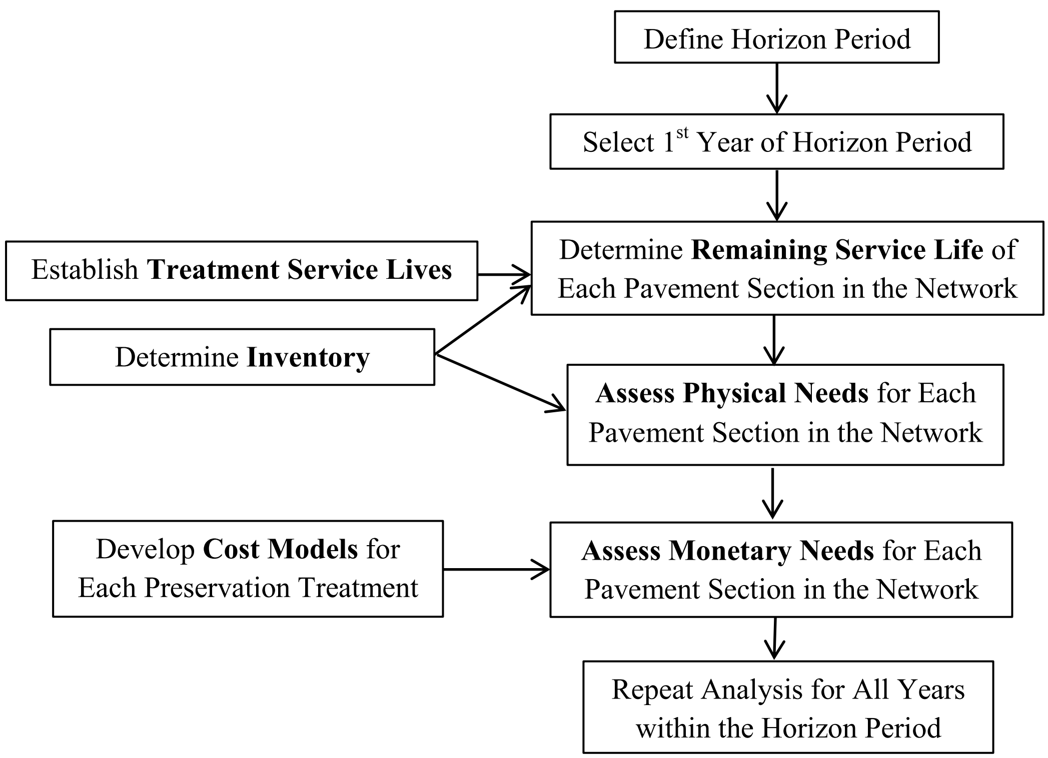


Figure 4.1 Framework for Pavement Preservation Needs Assessment on the Basis of Treatment Average Service Lives (Sinha and Labi, 2012)

The reliability of this age-based approach is limited because average service life estimates are used instead of specific performance predictions for each asset. Moreover, the uncertainty introduced in the analysis through the cost models and the treatment service life estimates increases the risk of inaccurate prediction of future needs.

In Section 3.6.3, a method for acquiring treatment service life estimates from mixed linear models was illustrated. These estimates are more accurate than the estimates acquired from simplistic – compared to the complex structure of pavement rehabilitation data – analyses, such as linear regression analysis. To investigate the sensitivity of the predicted preservation needs to changes in treatment service life estimates, the latter were first estimated using linear regression models and mixed linear models, each model type was used to estimate the future needs, and their results were compared with each other.

Tables 4.1 and 4.2 present the average service lives of six rehabilitation treatments applied to Indiana Interstates estimated from the linear regression model and the mixed linear performance model. The procedure for obtaining the service life estimates and the upper and lower bounds for service life was demonstrated in Section 3.6.3 for mixed linear models. The same procedure can be followed to obtain estimates from linear regression.

The service life results indicated that there is significant selectivity bias in the estimated performance models for some of the treatments. For example, the service life of PCC Overlay on PCCP, which is based on two contracts (but multiple pavement sections), was found to be very low using either of the two estimation methods. A closer look at the sample used for this treatment analysis showed that the treatment was applied in areas where the commercial vehicle traffic was very high, which probably caused the more rapid pavement deterioration. Thus, the average treatment service life is biased and refers only to pavement assets with high truck traffic. Moreover, the unusually high service life for the structural HMA overlay also seems to imply a self-selected sample.

Table 4.1 Rehabilitation Treatment Service Life Estimates and Bounds for Linear Regression Performance Models

| Rehabilitation Treatment | Rehabilitation Treatment Service Life | | |
|---|---|---|---|
| | Average | Lower Limit[a] | Upper Limit[b] |
| Preventive Maintenance (Thin HMA Overlay) | 12 | 11 | 13 |
| Structural HMA Overlay | 60 | 50 | 70 |
| Functional HMA Overlay | 18 | 17 | 19 |
| Repair PCC and HMA Overlay | 17 | 16 | 18 |
| Rubblize PCC/Composite and HMA Overlay | 31 | 27 | 35 |
| PCC Overlay on PCCP | 12 | 11 | 14 |

a Treatment age when the 95% upper limit of pavement performance reaches the pre-specified threshold (120 in/mile).

b Treatment age when the 95% lower limit of pavement performance reaches the pre-specified threshold (120 in/mile).

Table 4.2 Rehabilitation Treatment Service Life Estimates and Bounds for Mixed Linear Performance Models[a]

| Rehabilitation Treatment | Rehabilitation Treatment Service Life | | |
|---|---|---|---|
| | Average | Lower Limit[b] | Upper Limit[c] |
| Preventive Maintenance (Thin HMA Overlay) | 15.5 | 13 | 18.5 |
| Structural HMA Overlay | 32 | 24 | 40 |
| Functional HMA Overlay | 14 | 12.6 | 15.8 |
| Repair PCC and HMA Overlay | 23 | 20 | 26 |
| Rubblize PCC/Composite and HMA Overlay | 29.5 | 25 | 34 |
| PCC Overlay on PCCP | 12.5 | 9 | 20 |

a The modeling formulations and covariance structures used are the ones shown in Tables 3.10 and 3.11.

b Treatment age when the 95% upper limit of pavement performance reaches the pre-specified threshold (120 in/mile).

c Treatment age when the 95% lower limit of pavement performance reaches the pre-specified threshold (120 in/mile).

The average treatment service lives estimated on the basis of linear regression and mixed linear performance models are compared in Figure 4.2. The first noticeable item in Figure 4.2 is that the linear regression results for the structural HMA overlay are highly unreasonable. Moreover, the linear regression performance models for 50% of the treatments overestimated the service lives; and for the other 50%, the treatments underestimated the service lives (assuming that the mixed linear model results are more accurate), which showed that there was no specific trend in the loss of accuracy.

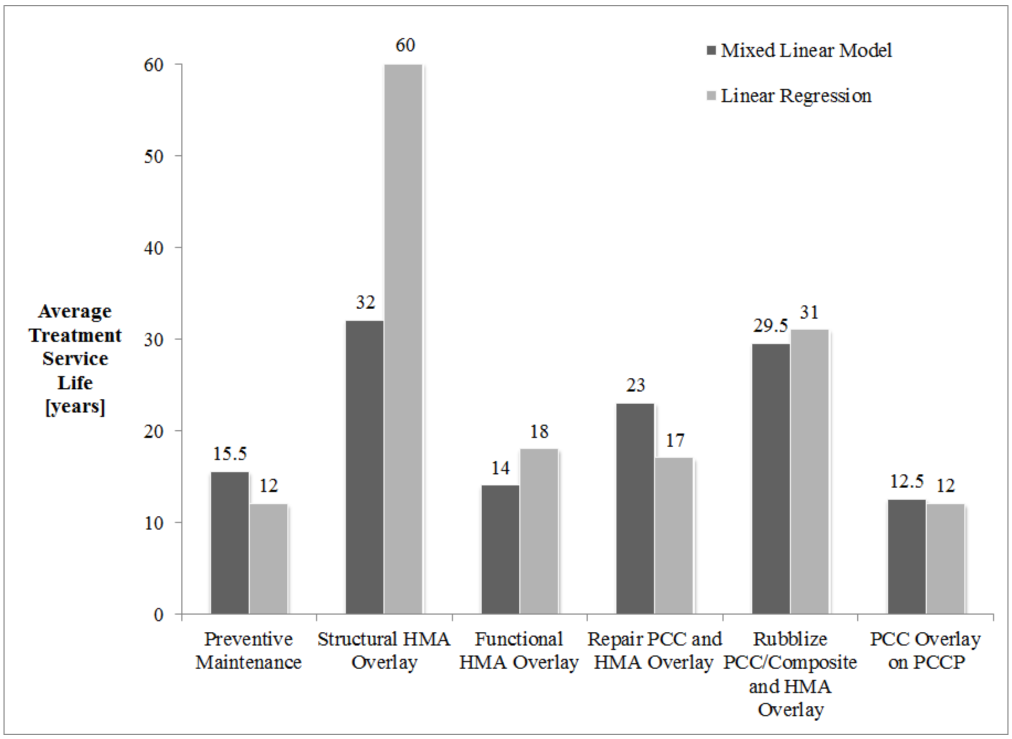


Figure 4.2 Comparison of Average Treatment Service Lives Obtained Using the Two Performance Modeling Techniques

The next step, using the average treatment service lives, was to identify the pavement assets that need to be preserved. The period 2010-2020 was the assumed horizon period, and the year of latest collected performance and traffic data was 2009). For this study, it was assumed that a pavement asset was going to be rehabilitated using the same treatment utilized at its last rehabilitation. Furthermore, this analysis did not cover the entire Indiana Interstate network, but rather only the Interstates rehabilitated from 1996 to 2006.

Table 4.3 shows the Indiana Interstate pavement sections that were rehabilitated during the period 1996-2006, and that had not been rehabilitated for a second time or reconstructed until 2009. The information shown in Table 4.3 is the only asset inventory information that was needed to perform this age-based needs assessment analysis.

Table 4.3 Indiana Interstate Rehabilitation Activities for the Period 1996-2006

| Rehabilitation | Number of Interstate Pavement Sections | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Treatment | Total | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 |
| Preventive Maintenance | 47 | | | 11 | 12 | 15 | | | 9 | | | |
| Structural HMA Overlay | 29 | | 10 | | 13 | | | | 6 | | | |
| Functional HMA Overlay | 95 | 16 | 14 | | 15 | 16 | | 25 | 5 | 4 | | |
| Repair PCC and HMA Overlay | 43 | 11 | 11 | | 8 | | | 8 | | 5 | | |
| Rubblize PCC/Composite and HMA Overlay | 33 | | 8 | 2 | | | | 8 | 15 | | | |
| PCC Overlay on PCCP | 8 | 2 | 6 | | | | | | | | | |
| Total | 255 | 29 | 49 | 13 | 48 | 31 | 0 | 41 | 35 | 9 | 0 | 0 |

Using the inventory information from Table 4.3 and the treatment service lives from Tables 4.1 and 4.2, the physical needs, based on the two methods of service life estimation (Linear Regression and Mixed Linear performance models), are presented in Tables 4.4 and 4.5.

Based on the results shown in Table 4.4, 171 Interstate pavement sections could be expected to need rehabilitation during the horizon period of 2010-2020. The results shown in Table 4.5 indicate that 170 pavement sections will need to be rehabilitated during 2010-2020. Thus, the difference between the total Interstate sections predicted by the two methods is not significant.

Table 4.4 Physical Needs[a] Assessment Based on Treatment Average Service Lives Estimated from Linear Regression Performance Models (Table 4.2)

| Rehabilitation | Number of Interstate Pavement Sections | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Treatment | Total | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| Preventive Maintenance | 47 | 11 | 12 | 15 | | | 9 | | | | | |
| Structural HMA Overlay | 0 | | | | | | | | | | | |
| Functional HMA Overlay | 86 | | | | | 16 | 14 | | 15 | 16 | | 25 |
| Repair PCC and HMA Overlay | 38 | | | | 11 | 11 | | 8 | | | 8 | |
| Rubblize PCC/Composite and HMA Overlay | 0 | | | | | | | | | | | |
| PCC Overlay on PCCP | 0 | | | | | | | | | | | |
| Total | 171 | 11 | 12 | 15 | 11 | 27 | 23 | 8 | 15 | 16 | 8 | 25 |

a Future needs for the Interstates rehabilitated from 1996 to 2006

Table 4.5 Physical Needs[a] Assessment Based on Treatment Average Service Lives Estimated from Mixed Linear Performance Models (Table 4.3)

| Rehabilitation | Number of Interstate Pavement Sections | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Treatment | Total | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| Preventive Maintenance | 47 | | | | | 11 | 12 | 15 | | | 9 | |
| Structural HMA Overlay | 0 | | | | | | | | | | | |
| Functional HMA Overlay | 95 | 16 | 14 | | 15 | 16 | | 25 | 5 | 4 | | |
| Repair PCC and HMA Overlay | 22 | | | | | | | | | | 11 | 11 |
| Rubblize PCC/Composite and HMA Overlay | 0 | | | | | | | | | | | |
| PCC Overlay on PCCP | 6 | 6 | | | | | | | | | | |
| Total | 170 | 22 | 14 | 0 | 15 | 27 | 12 | 40 | 5 | 4 | 20 | 11 |

a Future needs for the Interstates rehabilitated from 1996 to 2006

Figure 4.3 compares the annual physical needs on the basis of the two methods for acquiring service life estimates. For certain years, the difference between the needs predicted from the two methods is significant.

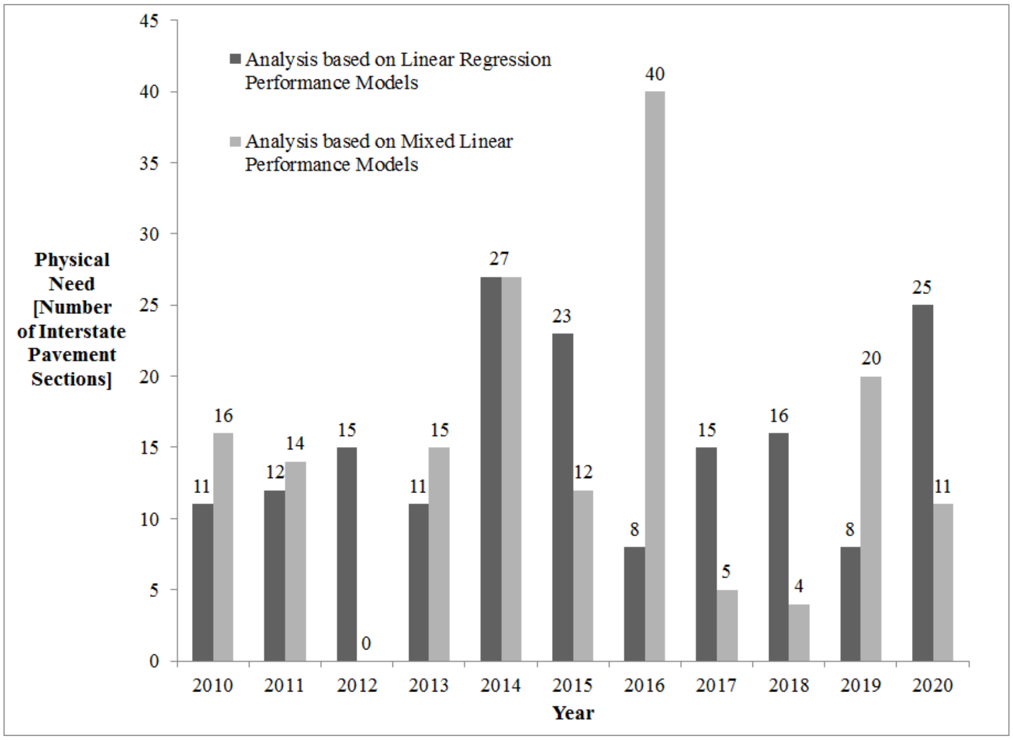


Figure 4.3 Comparison of Predicted Physical Rehabilitation Needs of Indiana Interstate Pavements on the Basis of Two Treatment Service Life Estimation Methods

The unit cost of each treatment for Interstates is estimated as the total contract cost of treatment applications divided by the number of rehabilitated miles (Table 4.6). Using the estimated physical needs (Tables 4.4 and 4.5) and the average unit costs presented in Table 4.6, the monetary needs for the Indiana Interstates analyzed in this study for the period 2010-2020 were estimated. Figures 4.4 and 4.5 present the annual and cumulative monetary needs based on the service life estimates acquired from the linear regression and mixed linear performance models, respectively.

Table 4.6 Unit Cost[a] of Rehabilitation Treatments Based on Interstate Applications

| Rehabilitation Treatment | Number of Contracts | Unit Cost per Interstate Pavement Section | | | |
|---|---|---|---|---|---|
| | | Average | Standard Deviation | Minimum | Maximum |
| Preventive Maintenance | 10 | $277,968 | $425,660 | $28,984 | $1,530,616 |
| Structural HMA Overlay | 5 | $401,649 | $441,370 | $ 41,597 | $1,100,522 |
| Functional HMA Overlay | 36 | $328,920 | $426,839 | $24,347 | $1,797,386 |
| Repair PCC and HMA Overlay | 12 | $1,290,499 | $858,795 | $147,296 | $2,737,662 |
| Rubblize PCC/Composite and HMA Overlay | 4 | $2,706,956 | $2,065,620 | $360,000 | $5,974,972 |
| PCC Overlay on PCCP | 2 | $5,552,922 | $1,331,677 | $4,611,284 | $6,494,559 |

a Source: 1996-2006 Data from INDOT Contracts Division

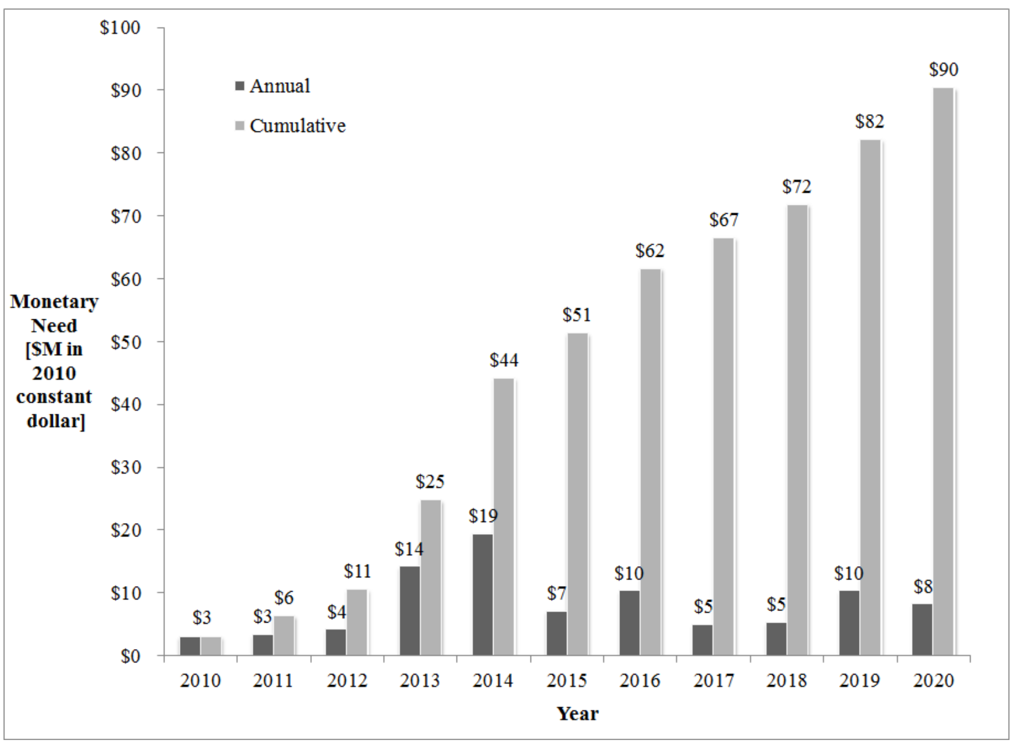


Figure 4.4 Annual and Cumulative Monetary Needs of Indiana Interstate Pavements on the Basis of Service Life Estimates from Linear Regression Performance Models

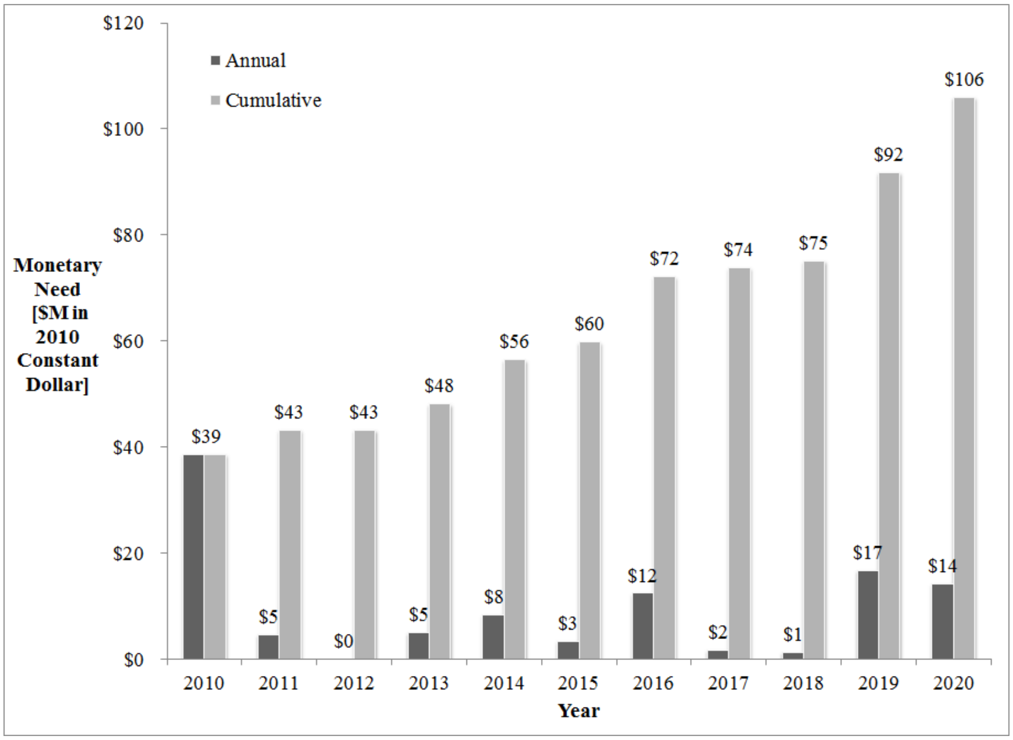


Figure 4.5 Annual and Cumulative Monetary Needs of Indiana Interstate Pavements on the Basis of Service Life Estimates from Mixed Linear Performance Models

Comparing the annual monetary needs resulting from the two different service life estimation methods would not be reasonable for the age-based needs assessment approach. The age-based approach is not expected to reliably predict the preservation needs on an annual basis. Thus, the reliability of the age-based monetary needs assessment may be higher if the results are aggregated in time periods.

Figure 4.6 compares the monetary needs for three time periods: (i) 2010-2014,( ii) 2015-2020, and (iii) 2010-2020. In the period 2010-2014, the monetary needs based on mixed model analysis were higher by 28%. However, the monetary needs for the period 2015-2020 were almost identical. If the error associated with the service lives estimates had a distinctive pattern, there also would be a pattern in the monetary needs results (i.e., the needs would be systematically underestimated or overestimated).

The conclusion regarding the age-based approach is that unless the treatment average service lives, which are estimated by a rather simplistic method, are found typically higher or typically lower from the unbiased service life estimates, there will be no significant change in the estimated monetary needs. As such, in this needs assessment analysis, the impact of the method of service life estimation was found to be minimal.

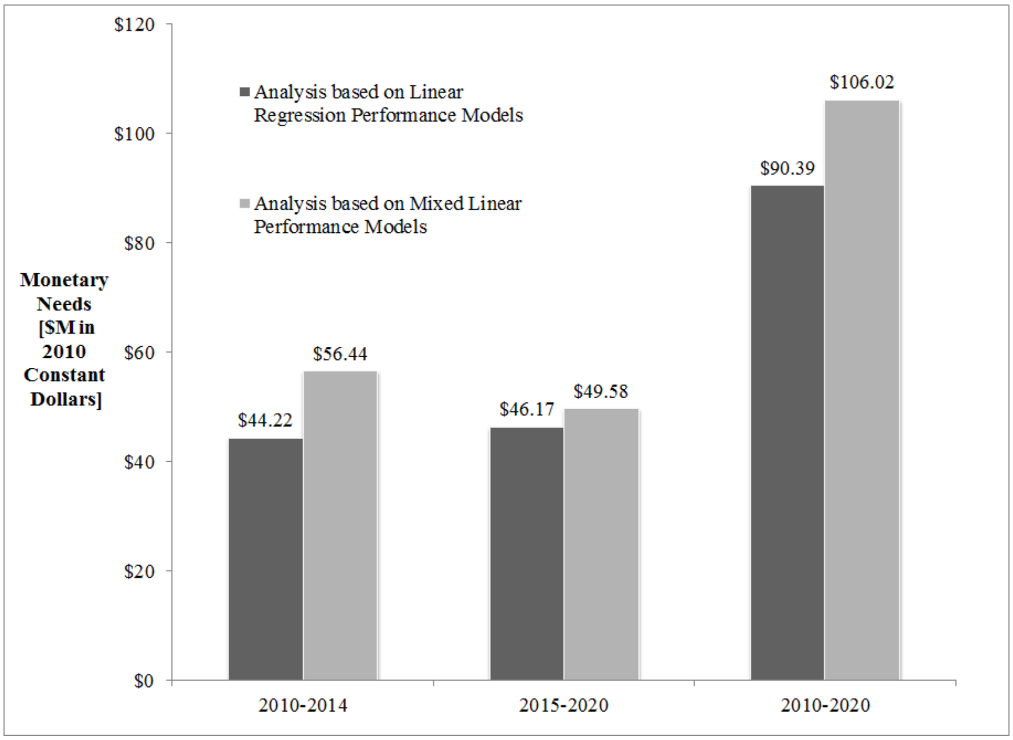


Figure 4.6 Comparison of Monetary Needs of Indiana Interstate Pavements on the Basis of Two Treatment Service Life Estimation Methods

## 4.3 Impact of Pavement Performance Prediction Method on Performance-based Needs Assessment Analysis

Pavement preservation needs can be assessed at the network level on the basis of the expected future performance of each pavement asset. This approach requires a well-maintained PMS database and performance models that can predict the pavement deterioration after the application of a preservation treatment. The performance-based approach is considered to be more reliable than the age-based approach since it does not utilize averages but rather uses specific predictions for each asset (Sinha and Labi, 2012).

In Chapter 3, it was shown that mixed models have the advantage of offering "personalized" predictions for each individual in the analysis sample using the BLUP method. This characteristic can be used for acquiring highly accurate performance predictions, which would improve the reliability of performance-based estimated needs. In this section, the impact of prediction accuracy at the pavement section level on the network-level needs assessment will be investigated. In this section, the future preservation needs of the Indiana Interstate pavements that had been rehabilitated during the period 1996-2006 are assessed using the BLUP method for obtaining performance predictions as described in Chapter 3, and are compared with the needs estimated using linear regression predictions.

Figure 4.7 presents the general framework for assessing future pavement preservation needs on the basis of performance trends (Sinha et al, 2005). The first step is to define a horizon year for the analysis. Next, the remaining service life is estimated for each pavement asset by obtaining performance predictions for each pavement asset specifically, and assuming a threshold that signifies performance failure and consequently the need for preservation. The physical needs of the network are then determined on the basis of the remaining service life estimation for each asset and the highway agency's decision-making process regarding the choice of the "most suitable" preservation treatment for each asset. Finally, preservation treatment cost models, either in the form of average values for each treatment category or actual models that estimate the cost based on the asset functional class, project scale, location etc., are used to obtain the monetary preservation needs for the horizon period.

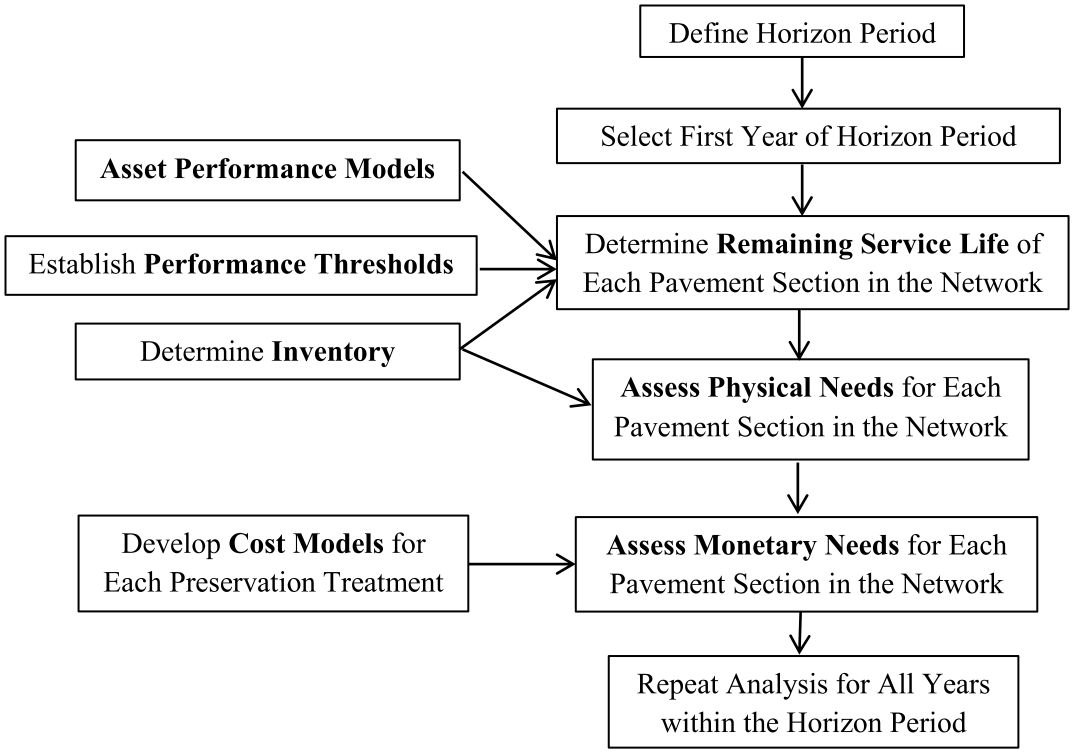


Figure 4.7 Framework for Pavement Preservation Needs Assessment Based on Performance-Predicted Trends (Sinha et al, 2005)

The reliability of the results produced by a performance-based needs assessment depends on the reliability of the performance predictions and cost estimates that serve as the key inputs in this analysis. The improvements in the reliability of performance predictions for post-rehabilitated pavements accomplished in this study reduce the uncertainty introduced to the needs assessment analysis. To investigate the impact of the pavement section-specific performance prediction method (presented in Section 3.6.4) on the network-level needs estimation, the physical and monetary needs for the Indiana Interstate pavements that had been rehabilitated during the period 1996-2006 and had not been rehabilitated for a second time or reconstructed until 2009 (inventory information presented in Table 4.3) were estimated using performance predictions from linear regression and mixed linear models.

As explained in Section 3.4.3, performance predictions acquired from linear regression do not take into account the unobserved heterogeneity that is responsible for a part of the unexplained variation of the pavement deterioration process at the contract and pavement section level. The BLUP method, which was used in this thesis for obtaining pavement-section-specific predictions in mixed linear models, was used for predicting the condition of the Indiana Interstate pavement sections presented in Table 4.3. The chosen mixed linear models formulations used in this analysis are those shown in Table 3.10.

As in the previous section, the period 2010-2020 was used as the horizon period, and it was assumed that each pavement asset would be rehabilitated using the same treatment received the last time that it was rehabilitated. Tables 4.7 and 4.8 present the physical needs estimated using IRI as the performance indicator on the basis of the two performance prediction methods: population-wide predictions from linear regression performance models and pavement-section-specific predictions from mixed linear performance models using the BLUP method.

Comparing the estimated physical needs from the two performance prediction methods, it can be seen that the total physical needs predicted by the linear regression models were fewer than the needs predicted by the mixed models. The estimated physical needs from the two methods are graphically compared in Figure 4.8.

Table 4.7 Physical Needs[a] Assessment on the Basis of Post-Rehabilitation Performance Predictions from Linear Regression Performance Models

| Rehabilitation Treatment | Number of Interstate Pavement Sections | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| Preventive Maintenance | 46 | 6 | 6 | 5 | 8 | 6 | 6 | 4 | 3 | 1 | 1 | |
| Structural HMA Overlay | 0 | | | | | | | | | | | |
| Functional HMA Overlay | 42 | | | | 1 | 2 | 2 | 4 | 7 | 9 | 7 | 10 |
| Repair PCC and HMA Overlay | 27 | | | 2 | 6 | 2 | 4 | 2 | 5 | 2 | 1 | 3 |
| Rubblize PCC/Composite and HMA Overlay | 5 | | | | | 1 | 1 | 1 | | 1 | 1 | |
| PCC Overlay on PCCP | 2 | | | | | | 1 | | | 1 | | |
| Total | 122 | 6 | 6 | 7 | 15 | 11 | 14 | 11 | 15 | 14 | 10 | 13 |

a Future needs for the Interstates rehabilitated from 1996 to 2006

Table 4.8 Physical Needs[a] Assessment on the Basis of Post-Rehabilitation Performance Predictions Acquired from the BLUP Method from Mixed Linear Performance Models

| Rehabilitation Treatment | Number of Interstate Pavement Sections | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| Preventive Maintenance | 42 | 6 | 5 | 5 | 4 | 6 | 4 | 3 | 1 | 1 | 4 | 3 |
| Structural HMA Overlay | 4 | | | 1 | | | | 1 | | 1 | 1 | |
| Functional HMA Overlay | 54 | 1 | 3 | 3 | 3 | 4 | 6 | 7 | 5 | 10 | 7 | 5 |
| Repair PCC and HMA Overlay | 31 | 1 | | 1 | 5 | 3 | 6 | 3 | 4 | 2 | 2 | 4 |
| Rubblize PCC/Composite and HMA Overlay | 4 | | | 1 | | | 1 | | | 1 | 1 | |
| PCC Overlay on PCCP | 3 | 1 | | | 1 | | | 1 | | | | |
| Total | 138 | 9 | 8 | 11 | 13 | 13 | 17 | 15 | 10 | 15 | 15 | 12 |

a Future needs for the Interstates rehabilitated from 1996 to 2006

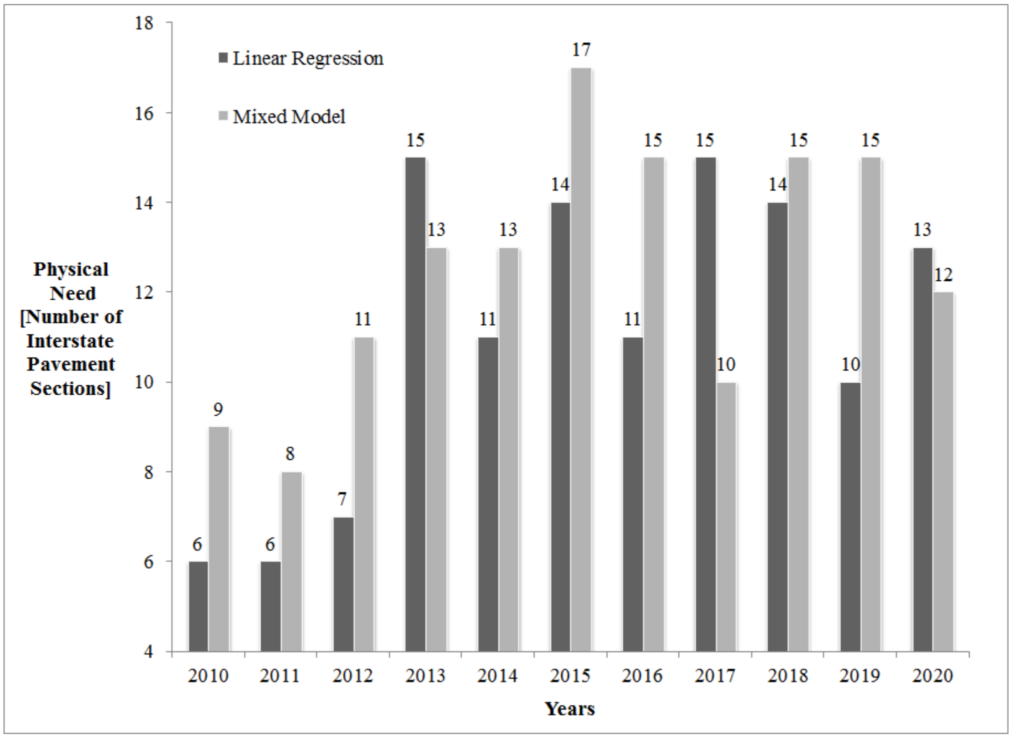


Figure 4.8 Comparison of Predicted Physical Needs of Indiana Interstate Pavements on the Basis of Two Performance Prediction Methods

The average unit cost of each treatment, for Interstates, is presented in Table 4.6. Using the estimated physical needs and the average rehabilitation treatment cost, the monetary needs for the period 2010-2020 were estimated and compared (Figure 4.9). The results indicate that the monetary needs based on the regression model predictions were lower at the beginning of the horizon period (2010-2013), which can be seen clearer in Figure 4.10. Only 65% of the monetary needs for the period 2010-2014 were predicted by linear regression (assuming that the predictions obtained from the BLUP method are accurate). The gap closed somewhat in the next period (2015-2020) due to pavement sections whose failures were not predicted in the first period but were predicted during the second period. Assuming the focus was on the entire horizon period, then linear regression underestimated the monetary needs by 12.6%.

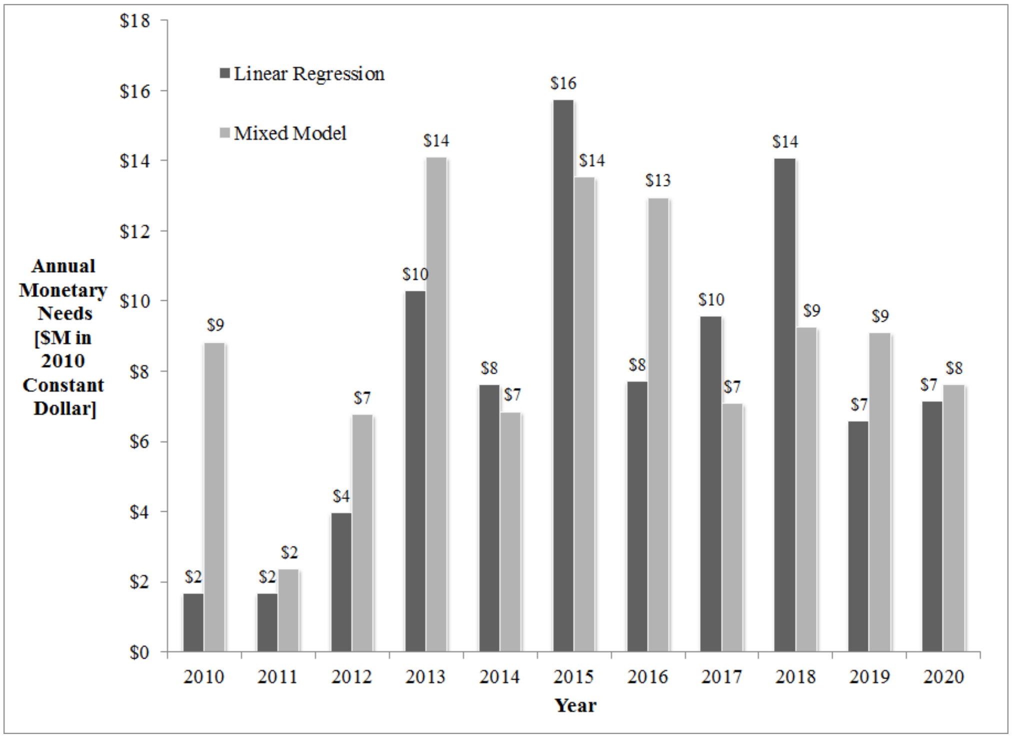


Figure 4.9 Comparison of Predicted Monetary Needs of Indiana Interstate Pavements on the Basis of Two Performance Prediction Methods

To conclude, the effect of the prediction accuracy on needs assessment was found higher for short-term monetary needs estimation. The needs were underestimated by 35%, which is a significant percentage. The long-term effect of the difference in model type on monetary needs was found to be relatively insignificant. However, the physical needs estimated from the mixed model performance models are superior and provided information on the exact assets that were in need of rehabilitation, taking into account any unobserved effects, which makes the performance-based needs assessment approach much more reliable.

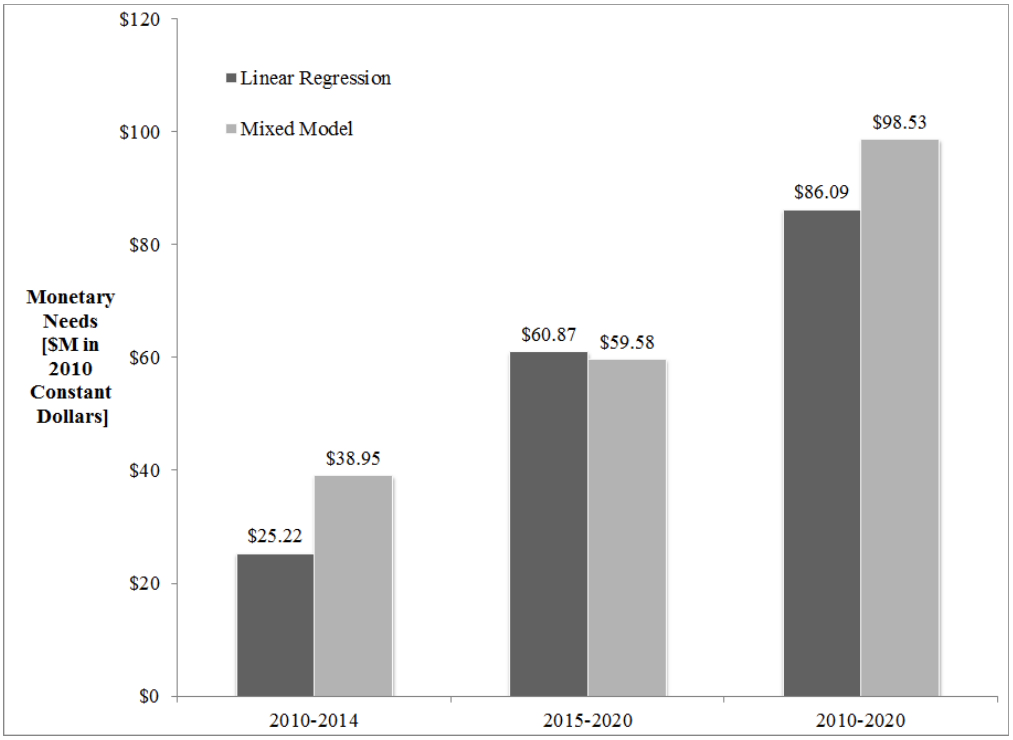


Figure 4.10 Comparison of Monetary Needs of Indiana Interstate Pavements on the Basis of Two Performance Prediction Methods

## 4.4 Chapter Summary

In this chapter, the impact of the methodological framework proposed in this study for pavement performance prediction on pavement preservation needs assessment was investigated for the age-based and the performance-based needs assessment approaches. The service lives and performance predictions resulting from the mixed linear models and linear regression analysis were compared to make inferences about the practical benefits of the proposed mixed model methodology.

It was found that, for the age-based approach, unless the treatments average service lives, which are estimated by a simplistic method, are found typically higher or typically lower from the unbiased service life estimates, there will be no significant change in the estimated monetary needs. Moreover, it was found that the effect of the prediction accuracy on the performance-based needs assessment was higher for the estimation of short-term monetary needs compared to long-term monetary needs.

Comparing all of the results from this chapter together in Figure 4.11, it can be concluded that there is no method that gives typically closer estimates to the performance-based mixed linear method, which is assumed to be the most accurate method for obtaining pavement-section-specific predictions. Even though the service life estimates that use mixed linear models are considered significantly less biased than those using linear regression, the age-based needs assessment approach cannot be recommended for PMS application because the resulting needs are not close to the actual future needs of the network. Thus, the only method from those presented here suggested for PMS application is the performance-based needs assessment approach, which used the BLUP method to predict pavement performance from mixed linear models.

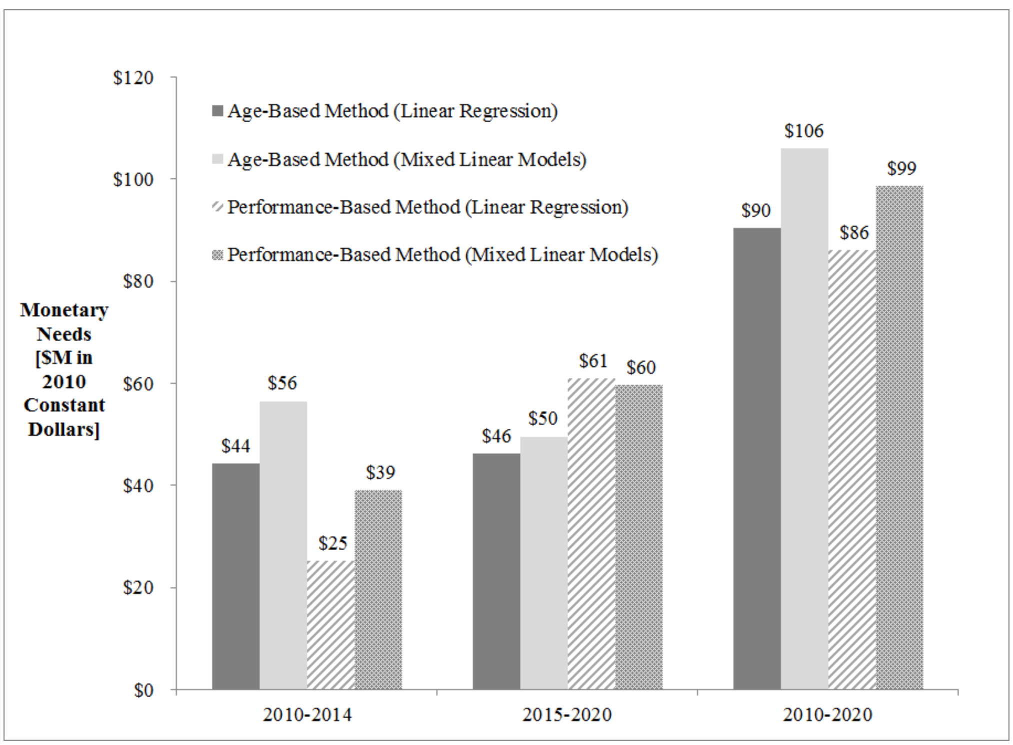


Figure 4.11 Comparison of Monetary Needs of Indiana Interstate Pavements on the Basis of the Four Displayed Methods

# CHAPTER 5 SUMMARY, CONCLUSIONS, AND FUTURE WORK

## 5.1 Summary

Reliable and effective treatment performance modeling techniques provide substantial benefits to a PMS. If the modeling technique is appropriately chosen on the basis of practicality, precision, the intended use of the model, and the nature of the pavement data, its applicability to PMS can be enhanced. Since the incorporation of performance modeling techniques in PMS in the 1970s, a variety of techniques have been investigated and/or implemented in PMS. However, in the area of treatment performance modeling, an enhanced framework is needed for post-rehabilitation performance prediction and service life estimation that can accommodate the peculiar nature of pavement data and allow for integration of the network and project management levels, while remaining practical and appropriate for PMS application.

This thesis focused on developing a methodological framework for rehabilitation treatment performance analysis, specifically for the requirements and purposes of pavement management (discussed in Section 3.1). To accomplish this objective, a general procedure was followed (Figure 1.2). As such, in selecting modeling techniques and assuming relevant formulations, the following three aspects were considered: (i) the previous relevant research and lessons learned from past practices in highway agencies, (ii) the characteristics of pavement rehabilitation data, (iii) the purposes and requirements of pavement management in terms of the input data from rehabilitation analysis. A literature review of the state of the practice and state of the art techniques and methods for predicting pavement deterioration and/or for estimating treatment service life was presented in Chapter 2. Then, the criteria for the selection of an appropriate modeling technique for rehabilitation treatment performance analysis to be incorporated into PMS were identified and were used to evaluate the previously-reviewed empirical modeling techniques. The peculiar nature of pavement rehabilitation data was described in Chapter 3, and that information was shown for a specific treatment in the form of a three-level nested structure: contracts (first level), pavement sections (second level), and performance measurements (third level). In the same chapter, the outcomes of rehabilitation treatment performance analysis that are essential for pavement management were identified.

Taking into consideration the previously-mentioned pieces of information, it was concluded that mixed models are the most appropriate technique to be used in pavement management for treatment performance analysis. The theory of mixed linear models was presented in Chapter 3, with a focus on the general formulation of the models, the available estimation approaches, and the prediction methods and their importance to pavement management.

Regarding the applicability of mixed linear models in PMS, two formulations were identified as relevant: (1) the one-way random effects model and (2) the three-level nested linear model. The necessity for serial correlation correction in repeated-measures pavement data was then discussed, and numerous covariance structures that can be used for this correction were presented. Rehabilitation data from applications of a single treatment to Indiana Interstates were used to demonstrate analytically the procedure for selecting a mixed model formulation, and the analysis of the covariance structure. Also, two methodologies based on two different types of analysis were explored. Regarding the performance prediction and service life estimation of in-service pavements that have been rehabilitated in the past (predictions conditional on a specific in-service pavement section), *Best Linear Unbiased Prediction* demonstrated high prediction reliability. This method provides pavement managers the ability to duly incorporate the "realized values" of the random effects associated with unobserved heterogeneity in the prediction process. The second approach, which uses "population-wide" predictions and estimates, was found to be more appropriate for obtaining predictions regarding pavement sections scheduled to be rehabilitated in the future and average treatment service life estimates.

Using multiple samples from different rehabilitation treatments, it was concluded that the three-level nested linear model with a first-order ante-dependence covariance structure is most appropriate for analyzing data regarding pavement rehabilitation treatment performance if there are no data availability constraints. The proposed methodological framework was presented in Figure 3.10; and the limitations of the framework in terms of performance indicator type, deterioration functional form, data availability, and statistical software were discussed in Section 3.9.

In Chapter 4, the impact of the methodological framework proposed in this thesis for pavement performance prediction on pavement preservation needs assessment was investigated for the age-based and performance-based needs assessment approaches. The resulting service lives and performance predictions from the mixed linear models and linear regression analysis were compared to make inferences about the proposed mixed model methodology. It was found that, for the age-based approach, unless the treatments average service lives, which are estimated by a simplistic method, are found typically higher or typically lower than the unbiased service life estimates, there will be no significant change in the estimated monetary needs. Moreover, it was found that the effect of the prediction accuracy on the performance-based needs assessment was higher for the estimation of short-term monetary needs compared to long-term monetary needs. Finally, the performance-based needs assessment approach, which used the Best Linear Unbiased Prediction method to predict pavement performance from mixed linear models, was suggested for PMS application.

## 5.2 Conclusions

This thesis contributed to the enhancement of rehabilitation treatment performance analysis for pavement management systems. The main research findings are summarized below:

- It was found that pavement rehabilitation data typically involves a three-level nested structure: information on a specific treatment appears in the form of numerous treatment applications (contracts); each contract is assumed to be comprised of multiple pavement sections; and for each pavement section, multiple condition measurements are available. Due to the existence of this structure, this thesis proposed a three-level nested linear model (Section 3.5.2) as a more appropriate formulation for rehabilitation performance analysis. This formulation assumes that observations within the same contract and observations within the same pavement section that belongs to a given contract share unobserved characteristics. The results from the case study suggest that the main source of unexplained variation is at the contract level, which implies that unobserved contract-related characteristics, such as construction quality, overlay thickness, and milling depth, play a significant role in post-rehabilitation performance. Furthermore, the pavement section-level variance was also found to be significant. Thus, using a more appropriate structure compared to previous research, the proposed formulation corrects for unobserved heterogeneity bias.

- The covariance structure of pavement repeated measures was analyzed because of the need to correct for serial correlation among the repeated measures within a pavement section, and the intent to identify one structure (for purposes of practicality) that can be an accurate representation of post-rehabilitated pavement. After testing different structures on multiple datasets, the first-order ante-dependence structure (Eq. 3.24) was generally appropriate for post-rehabilitation data if the sample size was large enough to allow the use of this structure. The appropriateness of this structure is based on the fact that variance among the measurements for the same year after rehabilitation is higher when the number of years after rehabilitation, to which the measurement of performance refers, is higher. This result implies that during the first years after rehabilitation, pavement performance varies less among pavement sections while many years after rehabilitation, there is much higher unexplained variation in performance among sections.

- It was shown that mixed models can offer two different kinds of predictions: conditional (specific to a pavement section) and unconditional (population-wide). Both techniques are of paramount importance with regard to PMS. The outputs from the application of these techniques are essential inputs for pavement management. The Best Linear Unbiased Prediction (BLUP) method offers reliable conditional predictions regarding the future performance and remaining service life of in-service previously-rehabilitated pavements, which can be used in performance-based future needs assessment for these pavements. Also, population-wide treatment performance and service life expectations can be used for project-level decision-making with respect to rehabilitation treatment selection, for age-based physical and monetary needs assessment, and for treatment effectiveness evaluation.

- It was realized that the presence of a decision-making procedure in treatment selection could introduce serious bias to the effort to compare the effectiveness of different treatments. Treatment service life estimates (Figure 4.2) indicated the possible existence of selectivity bias. More costly and structurally stronger treatments were found to have shorter service life compared to less costly and structurally weaker treatments. For example, the average service life of PCC overlay was found to be 12.5 years, while the average service life of thin HMA overlay was found to be 15.5 years. A closer look at the PCC overlay data revealed that the treatment was applied only in areas with very high commercial vehicle traffic, which probably caused more rapid pavement deterioration. The problem of selectivity bias in rehabilitation treatment analysis was emphasized in this thesis so that pavement managers are aware that the performance models and service life estimates may be conditional to the sample.

- This thesis also included evaluation of the impacts of the proposed performance prediction framework on future rehabilitation needs estimation. Specifically, the effect of more reliable predictions on the predicted network-level rehabilitation needs was investigated. For the age-based approach, unless the treatment average service lives, which are estimated by a simplistic method, are found to be systematically higher or lower from the unbiased service life estimates, there will be no significant change in the estimated monetary needs.

- Regarding the performance-based needs assessment, it was found that prediction reliability had a higher effect on the short-term (five-year horizon period) needs estimation. Actually, linear regression performance predictions resulted in a 35% underestimation of the short-term monetary needs, compared to mixed model predictions. The performance-based needs assessment approach, which used the BLUP method to predict pavement performance from mixed linear models, is proposed by this thesis as more reliable for PMS application compared to the other presented approaches.

- The proposed methodological framework (Figure 3.10) is designed to serve as a further improvement of the existing methods used for treatment performance prediction in highway agencies and also to serve as a catalyst for integrating project level and network level management. The framework will be further simplified (Figures 3.11 and 3.12) when data availability and statistical software limitations are overcome in the near future. This thesis demonstrated the analysis steps in great detail and developed the code used for the analysis in the Appendices to help in the understanding of the techniques used and facilitate their adoption by highway agencies. This analysis requires an updated and integrated PMS database, and updated post rehabilitation information is needed for every pavement asset. Also, every asset receiving a new treatment should be re-inserted in the database and coded differently so that interventions can be easily tracked. These database requirements could delay the implementation of the proposed framework in highway agencies. On the other hand, there is need for basic explanatory variables (e.g., age, ESALs and/or heavy truck traffic, and pre-treatment pavement condition) because unobserved variables that are constant within a contract or pavement section are taken into account through the model estimation.

## 5.3 Future Research

This thesis focused on pavement rehabilitation. The data used for illustration and configuration of the proposed methodology is from a selection of rehabilitation treatments applied to Indiana Interstates during the period 1996-2006. Also, the methodology was developed for using continuous performance indicators and for representing each treatment performance by a single performance indicator. Finally, the evaluation of the impacts of the proposed framework was restricted to network needs assessment. The following areas of future research were identified:

- Evaluation of the impacts of the proposed framework on asset valuation. The increased performance prediction reliability offered by the proposed framework may enhance the reliability of performance-based asset valuation approaches. A comparison between pavement asset values estimated using simplistic approaches and the values estimated using pavement section-specific predictions from mixed models could reveal any significant impact on asset valuation.

- The incorporation of seemingly unrelated equations in the existing framework. Previous research has proposed using a system of equations based on multiple performance indicators for pavement performance modeling (Prozzi and Hong, 2006; Anastasopoulos et al, 2012). Seemingly unrelated equations (SURE) could be investigated for use in the proposed framework in order to take into account the various performance indicators in pavement management to accomplish more effective decision-making.

- Expansion of the developed framework to preservation analysis of other linear highway assets, such as guardrails and pavement markings. The expansion of the framework would be beneficial to highway agencies as it could lead to the integration of asset management component systems in terms of the performance modeling technique.

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APPENDICES

# Appendix A

SAS 9.2 commands for the Linear Regression model presented in Section 3.6.1, Table 3.3:

- Ordinary Least Squares Estimation

```
proc reg data=tr213;
      model iri=age comm1 logpreiri ppt/clb;
      run;
```

- Restricted Maximum Likelihood Estimation

```
proc mixed data=tr213 method=REML covtest cl;
      model iri=age comm logpreiri ppt/solution;
run;
```

SAS 9.2 commands for the One-Way Random Effects model presented in Section 3.6.1, Table 3.4:

```
proc mixed data=tr213 method=REML covtest cl;
class id;
model iri=age comm ppt logpreiri/solution;
random id;
run;
```

SAS 9.2 commands for the Three-Level Nested Linear model presented in Section 3.6.1, Table 3.5:

```
proc mixed data=tr213 method=REML covtest cl;
class contract id;
model iri=age comm ppt logpreiri /solution ddfm=kr;
random contract id(contract)/ solution;
run;
```

# Appendix B

SAS 9.2 commands for the Three-Level Nested Linear Model under the assumption of Unstructured Covariance presented in Section 3.6.2, Equations 3.34-3.36:

```
proc mixed data=tr213 method=REML covtest cl scoring=5;
class id contract;
model iri=age comm ppt logpreiri /solution;
repeated / subject=id(contract) type=un r rcorr;
random contract;
ods output covparms=cov
      rcorr=corr;
run;
```

SAS 9.2 commands for the Three-Level Nested Linear Model under the assumption of First-Order Ante-Dependence Covariance Structure presented in Section 3.6.2, Equations 3.37-3.39 and Table 3.6:

```
proc mixed data=tr213 method=REML covtest cl;
class id contract;
model iri=age ppt logpreiri /solution;
repeated / subject=id(contract) type=ante(1) r rcorr;
random contract;
ods output covparms=cov
      rcorr=corr;
run;
```

## Appendix C

SAS 9.2 commands for the point estimates and confidence limits of the example presented in Section 3.6.3, page 68:

```
proc mixed data=tr213 method=REML covtest cl;
class id contract;
model iri=age ppt logpreiri /solution;
repeated / subject=id(contract) type=ante(1) r rcorr;
random contract;
estimate 'Rehabilition of a pavement section - Planning Stage'
intercept 1 age 15 ppt 40.24 logpreiri 2.072 / cl;
run;
```

SAS 9.2 commands for the average pavement performance estimates and 95% confidence limits presented in Section 3.6.3, Table 3.7:

```
proc mixed data=tr213 method=REML covtest cl;
class id contract;
model iri=age ppt logpreiri /solution;
repeated / subject=id(contract) type=ante(1) r rcorr;
random contract;
estimate 'average for year 12' intercept 1 age 12 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 13' intercept 1 age 13 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 14' intercept 1 age 14 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 15' intercept 1 age 15 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 16' intercept 1 age 16 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 17' intercept 1 age 17 ppt 41.0685 logpreiri
1.93098 / cl;
estimate 'average for year 18' intercept 1 age 18 ppt 41.0685 logpreiri
1.93098 / cl;
run;
```

SAS 9.2 commands for obtaining the Linear Regression predictions for Section 3.6.4, Table 3.8:

```
proc mixed data=tr213 method=REML covtest cl;
model iri=age comm ppt logpreiri/solution residual outpm=pred_mean;
run;
```

SAS 9.2 commands for obtaining the Three-Level Nested Linear Model predictions using the BLUP method for Section 3.6.4, Table 3.8:

```
proc mixed data=tr213 method=REML covtest cl;
class contract id;
model iri=age comm ppt logpreiri /solution residual ddfm=kr
outp=pred_BLUP_3ln outpm=pred_mean_3ln influence;
random contract id(contract)/ solution;
estimate 'I-74, mile 4-5, 2006' intercept 1 age 5 comm 6.89 ppt 38.13
logpreiri 2.102091 | contract 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
id(contract)0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0/
cl;
estimate 'I-74, mile 4-5, 2007' intercept 1 age 6 comm 6.95 ppt 38.13
logpreiri 2.102091 | contract 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
id(contract)0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0/
cl;
[….]
estimate 'I-74, mile 4-5, 2016' intercept 1 age 15 comm 8.43 ppt 38.13
logpreiri 2.102091 | contract 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
id(contract)0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0/
cl;
run;
```