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Development of an Empirical-Mechanistic Model of Overlay Crack Progression Using Data from the Washington State PMS Database

Authors:
Z. Nakat, S. Madanat, F. Farshidi, and J. Harvey

Report prepared for the California Department of Transportation through the Partnered Pavement Research Center Contract Strategic Plan Item 3.2.5: Documentation of Pavement Performance Data for Pavement Preservation Strategies and Evaluation of Cost-effectiveness of Such Strategies”

PREPARED FOR:

California Department of Transportation
Division of Research and Innovation
Sacramento

PREPARED BY:

University of California
Pavement Research Center
Berkeley and Davis

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Abstract: This is the second of two reports that present fatigue cracking performance models for asphalt concrete overlays placed on existing asphalt concrete pavement. The models were developed from the pavement management system (PMS) database of the Washington State Department of Transportation (WSDOT). The database included existing pavement structure, overlay thickness and type, truck traffic, and observed percent of the wheelpath cracked from annual condition surveys. Climate data was developed by the UCPRC to augment the WSDOT data. This report presents a model for crack propagation, starting from crack initiation, which was defined as 5 percent of the wheelpath with longitudinal cracking. The combined initiation and propagation models were included in a spreadsheet calculator which was used to perform an analysis of the sensitivity of crack initiation and propagation to the input variables. The models are extremely useful for predicting pavement performance. For use in California they will need recalibration of the coefficients to reflect differences in WSDOT and California practice, primarily the use of thicker overlays in California, placement of overlays at much more advanced states of cracking in the existing pavement, and possible differences in routine maintenance activities.

Keywords: fatigue cracking, performance models, pavement preservation, asphalt, pavement management

Proposals for Implementation:
Compare results calculated with models to observed performance from data available in the Caltrans PMS database; recalibrate models with better Caltrans PMS data once the database is improved; use models in Caltrans PMS.

Related documents:
UCPRC-RR-2005

Signatures:

Z. Nakat **First Author**	S. Madanat, J. Harvey **Technical Review**	D. Spinner **Editor**	J. Harvey **Principal Investigator**	T. J. Holland **Caltrans Contract Manager**

DISCLAIMER

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The Caltrans Division of Research and Innovation (DRI) Contract Manager was Michael Samadian, under the direction of Tom Hoover and Nick Burmas. The Pavement Standards Team Technical Lead was Shakir Shatnawi.

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PROJECT OBJECTIVES

This report was completed as part of Partnered Pavement Research Center (PPRC) Strategic Plan Element 3.2.5, titled “Documentation of pavement performance data for pavement preservation strategies and evaluation of cost-effectiveness of such strategies.” The main objective of this project was to develop Empirical-Mechanistic (E-M) performance models using data from Washington State’s Pavement Management System (PMS) databases. This report presents results of the development of an alligator cracking progression model.

EXECUTIVE SUMMARY

The work presented in this report was performed for the California Department of Transportation (Caltrans) by the University of California Pavement Research Center (UCPRC) as part of Partnered Pavement Research Center Strategic Plan Element 3.2.5 (PPRC SPE 3.2.5), titled "Documentation of pavement performance data for pavement preservation strategies and evaluation of cost-effectiveness of such strategies." Work on PPRC SPE 3.2.5 was begun in 2006. The Pavement Standards Team (PST) technical lead for PPRC SPE 3.2.5 is the Division of Maintenance.

An infrastructure management system (IMS) is a decision-support tools that aids public agencies in planning maintenance activities of their facilities. A complete IMS facilitates the following tasks: facility inspection and data collection, deterioration prediction through performance models, and selection of the maintenance, rehabilitation, and reconstruction (MR&R) policy over the planning horizon. A pavement management system (PMS) is an IMS used for pavement infrastructure. Pavement performance models are a core component of PMS.

The main objective of this project was to develop Empirical-Mechanistic (E-M) pavement performance models for predicting the initiation and progression of alligator cracking in hot-mix asphalt (HMA) overlays on asphalt pavements, using data from the Washington State Department of Transportation (WSDOT). The research described in this report complements the work performed in PPRC SPE 4.5, which involved development of empirical-mechanistic pavement performance models using data from the Washington State PMS database, which was published in report UCPRC-RR-2005-5. Along with the cracking initiation model described in that report, the cracking progression model described herein completes the HMA pavement performance model suite.

At the start of this work, models using pavement data from WSDOT and the Arizona Department of Transportation (ADOT) were attempted. The initial reasoning for using PMS data from those states is that they have measured pavement conditions consistently over a long period of time, and they have topographic features and climate similar to parts of California. Therefore, Caltrans could use models developed using data from those states to manage a subset of California's pavement infrastructure until the department develops the database needed to support model development. However, the research team found that the ADOT data were inappropriate for developing the performance models needed in this project, so only WSDOT pavement data were used in model development.

Cracking progression is a continuous process that represents the change in the percentage of cracking with time, under certain structural, traffic, and climate conditions. The prediction of cracking progression is very important for pavement management agencies, since the extent of crack progression reflects the structural condition of a pavement section and triggers maintenance, rehabilitation, and reconstruction (MR&R) activities. The main focus of this research is the progression of fatigue cracking (commonly referred to as "alligator cracking") rather than longitudinal cracking, since alligator cracking is an advanced stage of longitudinal cracking. Alligator cracking as defined in the WSDOT PMS is equivalent to the combination of Caltrans Type B and Type C Alligator Cracking. The extent of alligator cracking is defined in the same way in the WSDOT and Caltrans PMS data collection manuals, as the percent of the wheelpath in the section with alligator cracking.

The following tasks were performed in order to develop the alligator cracking progression model:

1. The WSDOT PMS databases were mined for the most relevant variables, including pavement section structure, traffic, surface condition, and resurfacing activities. These were augmented with environmental data obtained from external data sources.
2. Appropriate functional forms were selected for the performance model, and relevant explanatory variables were included.
3. Appropriate statistical modeling tools were used to correct for empirical data problems and estimate (calibrate) the parameters of the performance model.
4. Classical statistical tests were performed on the model to confirm the statistical significance of the various parameters and to test the model as a whole.
5. Predictions were performed using the performance model suite (crack initiation and progression) in order to confirm that it produced realistic results. The computations were implemented using microsimulation in order to capture the stochastic (i.e., random) nature of the overlay crack initiation process.

Conclusions from this research can be summarized as follows:

1. The developed performance model for cracking progression in HMA overlays on asphalt pavements is rich in relevant explanatory variables and produces good predictions. This overcomes several shortcomings that characterize current empirical cracking progression models.
2. The following explanatory variables were found to be the most relevant predictors of the annual increment in alligator cracking for HMA overlays on HMA pavements:
    - The alligator cracking in the previous year
    - The existing alligator cracking prior to the application of the (last) overlay

- The thicknesses of asphalt-treated, portland cement-treated, and untreated aggregate bases
- The thickness of the underlying HMA layers prior to application of the overlay
- The thickness of the overlay
- The two types of WSDOT conventional HMA materials, Type A [nearly identical specification as Caltrans Type A dense-graded asphalt concrete (DGAC)] and Type B (specification requiring somewhat better performance than Caltrans Type B DGAC, less than Caltrans Type A DGAC)
- The annual traffic loading in ESALs
- The annual precipitation
- The average daily minimum temperature during the coldest month (December) and the average daily maximum temperature during the hottest month (July)

The main recommendations contained in the report are:

1. The developed HMA pavement performance model suite (the cracking initiation model described in report UCPRC-RR-2005-5 and the cracking progression model described in this report) should be tested on California PMS data. These data can either be collected as part of a pilot project or mined from data in the Caltrans PMS database after that database has been populated with information collected over consistently segmented sections. If the results of the tests are positive, then Caltrans can essentially use these models as temporary HMA pavement performance models.
2. Once Caltrans has populated its PMS database with sufficiently extensive condition survey data, these developed HMA pavement models can be updated with the California data by using statistical fusion procedures, such as Bayesian updating.
3. The ultimate objective of the development of such models is to use them within an integrated PMS. The models can provide predictions to support MR&R planning at both the project and network levels. Therefore, to fully reap the benefits of its investment in this research, Caltrans should continue its efforts at modernizing its PMS.

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ABBREVIATIONS AND TERMS USED IN THE TEXT

ADOT	Arizona Department of Transportation
Caltrans	California Department of Transportation
GLS	Generalized Least Squares
GIS	Geographic information systems
GPS	Global Positioning System
HDM-III	Highway Design and Maintenance, World Bank’s
IMS	Infrastructure Management Systems
LSDV	Least Squares Dummy Variables
LCCA	Life-Cycle Cost Analysis
MR&R	Maintenance, Repair and Reconstruction
PPRC SPE 3.2.5/4.5	Partnered Pavement Research Center Strategic Plan Element 3.2.5/4.5
PCI	Pavement Condition Index
PCR	Pavement Condition Rating
PMS	Pavement Management System
PSI	Pavement Serviceability Index
PST	Pavement Standards Team
SN	Structural Number
UCPRC	University of California Pavement Research Center

1 INTRODUCTION

The work presented in this report was performed for the California Department of Transportation (Caltrans) by the University of California Pavement Research Center (UCPRC) as part of Partnered Pavement Research Center Strategic Plan Element 3.2.5 (PPRC SPE 3.2.5), titled "Documentation of pavement performance data for pavement preservation strategies and evaluation of cost-effectiveness of such strategies." Work on PPRC SPE 3.2.5 was begun in 2006. The Pavement Standards Team (PST) technical lead for PPRC SPE 3.2.5 is the Division of Maintenance.

An infrastructure management system (ISM) is a decision-support tool that aids public agencies in planning maintenance activities of their facilities. A complete IMS facilitates the following tasks: facility inspection and data collection, deterioration prediction through performance models, and Maintenance, Repair, and Reconstruction (MR&R) policy selection over the planning horizon.

Several IMSs have been developed and applied to actual infrastructure networks. The Arizona Pavement Management System (PMS) was implemented in the 1980s with estimated savings of about $200 million in maintenance and rehabilitation costs in five years (1). Pontis, a system for maintenance optimization and improvement of a bridge network, has been used effectively for bridge improvement and maintenance planning in 40 states in the US (2). In California, $188 million of pavement rehabilitation contracts were awarded in the 2002–03 fiscal year (3). There is a potential for these expenses to be reduced if an IMS is developed and implemented.

Performance models are a core component of a PMS. There are two types of empirical performance models used in a PMS: models based on field data, and those based on experimental data. Experimental data are likely to suffer from biases as they do not represent the true deterioration mechanisms of pavements. Data from actual in-service pavement sections subjected to the combined actions of highway traffic and environmental conditions are more representative of the actual deterioration process. However, models based on field data also have some limitations. The most common problems encountered in models developed from in-service pavement sections are caused by unobserved events, such as data censoring, the presence of serial correlation among contiguous sections, and biases caused by the use of endogenous variables as explanatory variables (4). These problems can be addressed using proper statistical techniques such as those that will be discussed in this research.

The main objective of this research is to develop Empirical-Mechanistic (E-M) models for initiation and progression of overlay cracking in asphalt pavements, using data from the Washington State Department of Transportation (WSDOT) PMS databases. Overlay cracking occurs due to a combination of different types of cracking such as: thermal cracking which is due to extreme cold temperatures, fatigue cracking which is caused by traffic stresses, and reflection cracking which is a form of fatigue cracking that results in the propagation of cracking from underlying asphalt layers upwards through the asphalt overlay under traffic and climate stresses. The literature contains very little research on the subject of overlay cracking.

E-M models are deductive models where the functional form and specification (choice of explanatory variables) are based on physical considerations, and where the model parameters (coefficients) are calibrated by using empirical data and statistical estimation procedures. E-M models are discussed in detail in Appendix B.

The research described in this report extends the work performed in PPRC SPE 4.5, which involved development of empirical-mechanistic pavement performance models using data from the Washington State PMS databases. That work included development of a model for crack initiation in asphalt overlays of asphalt pavements, in terms of Equivalent Single Axle Loads (ESALs) to Five Percent Cracking of any type in the wheelpaths, including the WSDOT PMS equivalents of alligator cracking Types A, B, and C as defined in the Caltrans PMS. That research was published in report UCPRC-RR-2005-5 (5).

The remainder of this report is organized as follows: Chapter 2 presents an overview of the major components of a PMS. Chapter 3 discusses the development of a panel data overlay crack progression model. Panel data problems, such as incidental truncations, left censoring, and cross-sectional heterogeneity, are properly addressed and suitable statistical tools are applied. Chapter 4 presents the final conclusions resulting from this report, and discusses recommended future research to follow this work. Appendix A contains an explanation of the spreadsheet application of the models presented in this report. Appendix B contains a detailed literature review and discussion of performance models for pavement management systems.

2 THE ROLE OF PERFORMANCE MODELS IN PAVEMENT MANAGEMENT SYSTEMS

This chapter presents an overview of the major components of pavement management systems and the role of pavement performance models. A detailed literature review of pavement performance models is presented in Appendix B.

Since their introduction in the late 1960s and early 1970s, pavement management systems (PMSs) have evolved continuously in their scope, methodology, and application. PMSs were conceived in response to the shift from the deployment mode to the repair and maintain mode. At that time, the United States' network of freeways and major highways was almost complete, and a major responsibility for highway agencies was to preserve the huge investment in the pavements. As resources available for pavement maintenance were becoming scarcer, the number of pavement miles in need of repair or rehabilitation was increasing because of damage caused by such factors as aging and heavier traffic. This situation created an increasing backlog of pavement maintenance needs, and pavement engineers and planners believed that a systems approach could provide answers leading to more cost effective use of available resources.

The early systems used simple data-processing methods to evaluate and rank candidate pavement rehabilitation projects on the basis of such factors as current pavement condition and traffic. Forecasting of future pavement conditions was not considered, and no economic analysis of preventive versus deferred maintenance was performed. These were project-level systems that evaluated project priorities but did not formally address network-level planning issues such as the impact of limited budgets and desired performance goals for a complete roadway network. This is status of the current Caltrans PMS.

The network perspective was formally incorporated in the systems developed in the early 1980s, and the first such system was developed for the Arizona Department of Transportation (ADOT) (6). Systems developed in the 1990s use integrated techniques of performance prediction, network and project-level optimization, multicomponent prioritization, and geographic information systems (GIS) (7, 8, 9, 10, 11). Early systems focused on developing a pavement rehabilitation program for a single planning year. Priorities for rehabilitation typically were based on such factors as current pavement distresses, pavement age, and auto and truck traffic levels. The current Caltrans PMS performs this function.

The current generation of PMSs focuses on developing a multiyear program based on both current and projected pavement conditions. Candidate projects are identified for each year of a multiyear planning horizon, annual budgets are estimated, and the annual network performance is projected for percentages of roadway miles in good and poor pavement conditions.

In the future, it is likely that PMSs will provide integrated multiyear programs for multiple components of a roadway network (such as pavements and bridges). One can also envision PMS programs integrated with management systems for multimodal infrastructure facilities that include railroads, transit, airports, and harbors (12).

The following sections of this chapter briefly summarize the major components of a pavement management system:

- Data collection and management
- Pavement performance prediction
- Economic analysis and life cycle cost analysis
- Optimization

The relationship of each of these components in the development of a PMS with all of these capabilities is summarized in Figure 1. The figure shows the PMS as a pyramid. The first requirement for the PMS is adequate data collection and management, particularly the ability to access each of the data elements shown in the first level of the PMS and to relate them to each other in terms of time and location. The next level, which requires implementation of the first level, is the development of pavement performance models, such as the model described in the next chapter of this report. Once pavement performance prediction models are developed, better economic and life-cycle cost analysis can be performed. The final step is optimization of life-cycle cost for the network, and development of optimal maintenance and rehabilitation strategy selection and timing policies.

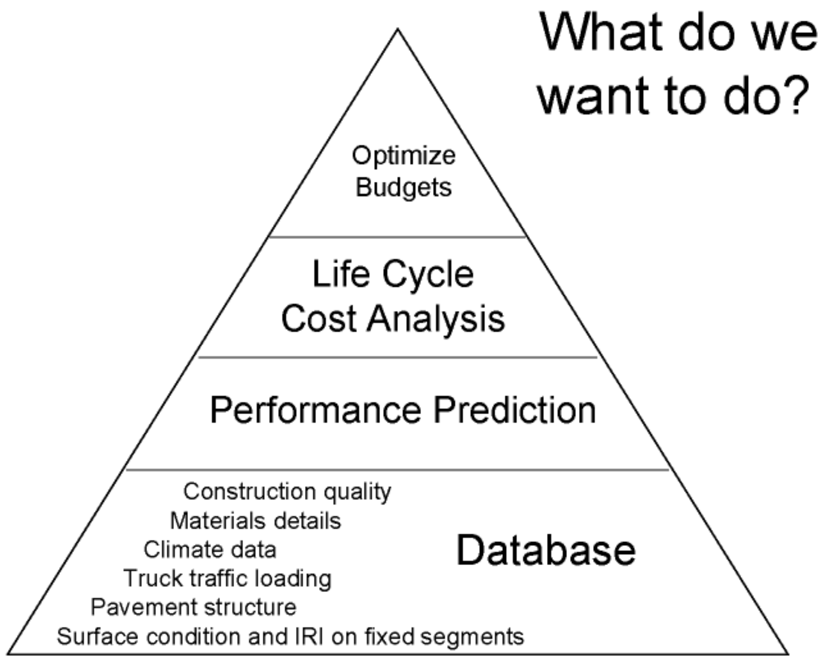

Figure 1: Conceptual relation of elements of modern PMS.

2.1 Data Collection and Management

The development of a sound PMS is conditional on the collection and management of a detailed and complete database. Early PMSs relied on subjective ratings of pavement condition; quantitative data on pavement distresses generally were not collected. Today, relational database software systems provide efficient methods for linking, sorting, analyzing, and organizing data. Equipment-based measurements of the severity and extent of different pavement distresses are now common practice for conducting pavement condition surveys for many important variables needed. Many agencies use a GIS to store location-referenced spatial data. This practice allows the user to connect multiple data items (such as pavement condition, design and construction data, traffic, and accident history) to specific links or nodes of a roadway network.

In the near future, greater automation of pavement condition surveys is expected. Equipment and software that use the concepts of artificial intelligence and digital imaging are likely to be available to collect data on most pavement distresses, including different types of cracking. The Global Positioning System (GPS) will be increasingly used to provide location referencing to elements of infrastructure facilities, thus allowing greater and more efficient use of GIS. Another future direction for database applications is Internet or intranet access to data and results. Such access will facilitate the use of the data and analysis results by a variety of user groups and agency policy makers and management. (12)

Recommendations for database elements for the Caltrans PMS needed to support pavement performance prediction models have been made in two other UCPRC reports for Caltrans (5, 13). Reports by Cambria (14, 15) identified the status of current Caltrans data collection and accessibility with respect to the needs for a modern PMS. The Cambria Systems reports considered the information provided in the UCPRC reports.

2.2 Pavement Performance Prediction

The prediction of pavement performance is the most essential element in a modern PMS, and reliable pavement performance prediction models are crucial for identifying the least-cost rehabilitation strategies that maintain desired levels of pavement performance.

Early systems did not have a predictive element, and they evaluated only current pavement conditions. Relatively simple prediction models were later introduced that often considered age as the only predictive variable. These models generally were based on engineering judgment to estimate the expected design life of different rehabilitation actions. This is the status of the current Caltrans PMS.

More modern systems use a variety of performance models. Some are based on empirical analysis of pavement condition survey data in which the potential predictive variables include traffic loading, climatic conditions, pavement structural properties, and history of pavement condition. Other models use mechanistic principles in which the pavement structure is modeled as a multilayered system subjected to traffic loading, the structural response of the pavement is calculated, and a damage accumulation model is developed to predict the time or cumulative traffic to reach a structural failure criterion (16). Different types of performance models are discussed in detail in Appendix B.

2.3 Economic Analysis and Life-Cycle Cost Analysis

The economic analysis element involves quantifying the various components of cost for alternative rehabilitation strategies so that the least-cost strategy can be identified. Early systems used only the initial construction costs of rehabilitation actions. Candidate projects were ranked on the basis of some simple measure (such as a weighted index of current distresses, for example a Pavement Condition Index [PCI]), and projects were selected by moving through this list until the entire construction budget was used. User costs were not analyzed, and life-cycle costs were not calculated. This is often referred to as a "worst first" method of prioritization in which the worst pavements get first priority, often with some weighting for economic importance, such as the Maintenance Service Level criteria included in the current Caltrans PMS prioritization matrix.

More modern systems analyze both agency costs and user costs. All future costs are converted to their present-worth costs and summed to obtain the total life-cycle cost of each alternative strategy. A likely future enhancement is the development of better user cost models and methods of calculating factors that cause user cost, such as construction-related traffic delay and safety, and vehicle operating costs. (Inclusion of better methods of calculating traffic delay for use in life-cycle cost analysis is part of the recent life-cycle cost analysis manual developed for Caltrans as part of PPRC SPE 4.15).

The current vehicle operating cost models are based on data from pavement studies conducted in developing countries. The range of pavement roughness in these studies is much larger than that reflected in the U.S. highway network. Additional data on user costs on U.S. highways will continue to be collected. Two types of user cost data will be compiled. One type of data relates to the impact of pavement roughness on speed profiles and vehicle operating and maintenance costs. The other type of data relates to the impact of traffic congestion and detours caused by construction activities. These data will be used to develop user cost models that are more representative of conditions on U.S. highways (12).

At the current time, highway agencies are increasingly moving toward the use of life-cycle concepts in planning and budgeting for their pavement investments. In fact, life-cycle concepts have been advocated or used widely within and outside the maintenance arena to study treatment effectiveness or to identify specific types and/or timings of pavement rehabilitation or reconstruction (17, 18, 19, 20, 21, 22). In a study that developed decision trees for selecting specific pavement preservation strategies, effectiveness was measured on the basis of extra service life and the equivalent annual cost of the strategy (23). In Indiana, past life-cycle cost analysis (LCCA) based studies of maintenance cost effectiveness were carried out by Mouaket et al. (24) and Al-Mansour and Sinha (25). Using various problem formulations, a number of researchers have sought to identify the optimal frequency of pavement interventions or identification of specific treatment actions over construction life cycle or rehabilitation life cycle (26, 27, 28, 29, 30, 31, 32, 33, 34). These studies have focused on reconstruction life cycles and/or sought to determine the specific types and timings of specific rehabilitation (resurfacing) treatments over such periods.

Pavement management agencies are also grappling with the integration of maintenance programs into their existing pavement management systems. Consistent with such issues is the practice of pavement preservation which involves application of maintenance prior to the onset of significant deterioration. Pavement preservation, which is also referred to as “preventive maintenance” in the literature and is deservedly getting attention among highway pavement managers, potentially increases average pavement performance and service life, and shows much promise in reducing long-term costs of highway facilities (35, 36, 37, 38). However, a pertinent issue is the extent to which pavement preservation extends the pavement service life. Related to this issue is the balancing act associated with pavement preservation application between sustained performance on the one hand and increased maintenance costs on the other (39).

The dilemma facing pavement network managers is as follows: if pavement preservation is applied too infrequently, user costs and reactive maintenance costs increase and overall life-cycle costs can be very high. On the other hand, if pavement preservation is applied too frequently, it is uneconomical because the excessive expenditure outweighs the additional benefits of extended pavement life and increased average pavement condition, and each preventive maintenance activity may incur construction-related user delay costs.

In a conceptual illustration that illustrates such a trade-off, Mamlouk and Zaniewski (38) implied that increasing pavement preservation effort (represented as frequency of pavement preservation treatments or reciprocal of pavement preservation treatment intervals) leads to increasing cost-effectiveness up to a point after which it leads to decreasing cost effectiveness. Agencies seek the level of pavement preservation expenditure that corresponds to maximum cost effectiveness for each pavement class. Such knowledge is useful for network-level pavement management, and preservation needs assessment and budgeting. Long-term effectiveness of pavement maintenance has generally been measured in terms of the monetary cost reduction associated with enhanced vehicle operation on an improved pavement, extension in pavement life, or increase in average pavement condition.

2.4 Optimization

The optimization element of a PMS involves using mathematical methods to identify the optimal pavement rehabilitation policies. These methods can be used to maximize some measure of benefit subject to meeting budgetary and other applicable policy constraints or to minimize the total cost subject to meeting specified performance goals and policy constraints.

Early systems were based on simple priority ranking methods and formal optimization models had not yet been developed. In the 1980s, some use of optimization models was initiated, and the initial focus was on project-level decision-making. The first network-level optimization model was employed in the PMS developed for the Arizona Department of Transportation (ADOT) (6, 40). For this system, a Markov Decision Process was used to model pavement decision-making, and a large-scale linear program algorithm was used to obtain the optimal pavement rehabilitation policies. After the successful application of the Arizona system, several other systems were developed by using the same or similar techniques of network optimization, such as the PMS developed for the Kansas Department of Transportation (41). Still, the use of formal optimization models, particularly at the network level, is rather limited at this time.

The two basic formulations for the optimization models are top-down and bottom-up. The top-down formulation provides a simultaneous analysis of an entire roadway network. The first step is to aggregate pavements having similar structure, traffic loading, and environment into mutually exclusive and collectively exhaustive homogeneous groups. Individual road segments are not represented in the optimization; instead, the units of analysis are the fractions of the groups in specific condition states. As a result, much of the segment-specific information (history of construction, rehabilitation, and maintenance; materials; structural details) is lost.

The user specifies network performance goals and available maintenance, rehabilitation, and reconstruction (MR&R) budgets. The objective of the optimization model is to find the optimal network MR&R polices that maximize benefits or minimize costs subject to meeting budgetary and policy constraints. These optimal network policies then guide the selection of actual projects for rehabilitation (6).

The main advantage of the top-down approach is that it allows the user to properly address the trade-off between rehabilitation and pavement preservation. That is, should a fixed budget be allocated to rehabilitation of a small number of segments or to pavement preservation of a larger number of segments?

The main disadvantage of the top-down approach is that it does not specify optimal activities for individual segments: the mapping of optimal network policies to facility activities is left to district managers. On the other hand, this gives engineers latitude in using their judgment, which is needed to compensate for the loss of pavement-segment information in the aggregation step.

The bottom-up approach can be formulated in several ways. The most logical formulation consists of the following steps: first, select a small set of optimal (or close-to optimal) sequences of MR&R activities for each facility, covering the desired planning horizon. Then, for a fixed budget, select the combination of sequences (one for each facility) that meets the budget constraint while optimizing a network-wide objective (42).

The main advantage of the bottom-up approach is that it preserves the identity of individual roadway segments, with all its information (structure, materials, history of construction, MR&R and traffic loading, environment). The main disadvantage of the bottom-up approach is that it lends itself to setting performance goals for individual projects rather than for the entire network.

3 DEVELOPMENT OF A PROGRESSION MODEL FOR ALLIGATOR CRACKING

3.1 Introduction

This chapter presents the development of the progression model for alligator cracking of asphalt concrete overlays using the Washington State Department of Transportation Pavement Management System (WSDOT PMS) database. The progression of alligator cracking is a continuous process and represents the change in the percentage of the wheelpath cracked with time under certain structural, traffic, and climate conditions. Crack progression occurs due to the combination of the following conditions: the widening and propagation of those cracks that have already initiated, the initiation of new cracks, and the propagation of cracks from past layers up to the surface of the new overlay (known as reflection cracking).

The prediction of crack progression is very important for pavement management agencies since the extent of crack progression reflects the structural condition of a pavement section and triggers maintenance and rehabilitation activities. The primary focus of this research is on the progression of alligator cracking rather than longitudinal cracking since the former is an advanced stage of the latter.

Obtaining sound empirical progression models with reasonable prediction capabilities, and estimated with a rich and relevant set of explanatory variables, has been a challenge for pavement engineers. In fact, the development of proper progression models requires having a data set constructed from detailed and accurate condition surveys. Given the nature of condition surveys, which are highly subjective, obtaining such data has always been a major obstacle. While the development of duration models, as discussed in Appendix B, requires advanced and sophisticated econometric techniques in comparison to progression models, the former is less demanding in terms of the quality of the condition surveys. This results from the fact that duration models represent the life of pavement overlays to a certain cracking threshold, which only requires measurement of the time when this cracking threshold is crossed, in contrast to progression models that require continuous measurements of the development of cracking of the overlay in terms of percent of wheelpaths cracked.

In the following sections of this chapter it will be shown that developing sound empirical progression models is possible using relatively accurate condition surveys and applying proper econometric techniques. First, the methodology used to develop a sound empirical progression model will be shown.

Second, the model that was developed using data from the WSDOT condition surveys will be presented. Finally, the model will be used to make predictions of the progression of alligator cracking in time.

3.2 Methodology

Pavement crack initiation and crack progression represent two different physical phenomena and need to be modeled separately. Crack initiation is a stochastic process that signals the beginning of cracking in pavement sections, while crack progression is a continuous process that occurs due to the propagation and widening of those cracks that have initiated, as well as to the initiation of further cracks. Thus the occurrence of crack progression is conditional on the occurrence of crack initiation, and needs to be modeled separately. In addition, having separate models for crack initiation and crack progression is more appropriate from a statistical point in view. In fact, prior to the initiation of cracking, pavement sections have zero cracking, resulting in a spike of zero values in a histogram of crack percentage for the sample. These structural zero values will have a dominant effect on the estimated parameters of the progression model. The progression model will thus predict poorly, especially for those sections where cracking progresses significantly beyond the initiation threshold.

An initiation model that describes the condition of pavement sections prior to the occurrence of cracking will account for the zero values, while the progression model is estimated for only those sections that have passed the crack initiation threshold, which results in better predictions. This modeling approach however introduces the problem of incidental truncation that will be discussed in more detail later in this chapter.

The dependent variable in the previously developed crack initiation model (5) was the distribution of the time (or number of accumulated Equivalent Single Axle Loads [ESALs]) to a cracking threshold (combination of any longitudinal or alligator cracking in five percent of the wheelpaths). Longitudinal cracking as defined in the WSDOT PMS is equivalent to Type A alligator cracking in the Caltrans PMS. Alligator cracking as defined in the WSDOT PMS is equivalent to the combination of Caltrans Type B and Type C alligator cracking. The extent of alligator cracking is defined in the same way in the WSDOT and Caltrans PMS data collection manuals, as the percent of the wheelpath in the section with alligator cracking.

Calculating the value of the dependent variable required recording the year when cracking occurred (complete observations) or the last year of the condition survey (censored observations) for every pavement section. The resulting sample was thus a cross-sectional data set.

For crack progression, the dependent variable is the change in the percentage of alligator cracking over the years for every section where cracking has already initiated. Thus for every section *that has cracked*, observations are needed of the yearly change in alligator cracking percentage from the time that initiation has started, to the time of the last survey. The data for the progression model therefore have a panel structure.

A panel, or longitudinal, data set is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample. Panel data sets possess several major advantages over conventional cross-sectional or time-series data sets. Panel data usually give the researcher a large number of data points, increasing the degrees of freedom and reducing the collinearity among explanatory variables, hence improving the efficiency of econometric estimates. More importantly, longitudinal data allow a researcher to analyze a number of important questions, such as the progression of cracking in time for different pavement sections, that cannot be addressed properly using cross-sectional or time-series data sets.

Compared with cross-sectional or time-series data, panel data raise new specification issues that need to be considered during the analysis. The most important of these is heterogeneity bias. Heterogeneity refers to the differences across cross-sectional units that may not be appropriately reflected in the available explanatory variables. If heterogeneity across cross-sectional units is not accounted for in the model, estimated parameters are biased because they capture part of the heterogeneity. In fact, cross-sectional heterogeneity is the central focus of panel data analysis. More details on panel data models and their specifications are discussed in Section 3.3.1.

Incidental truncation, or selection bias, arises in the estimation of empirical crack progression models due to the fact that crack progression is observed only after crack initiation has occurred. In other words, crack progression is only observed in weaker sections that have already failed according to the crack initiation criteria. The sample selection problem will result in an over representation of the weak sections in the sample, and the estimated parameters will have a downward bias. This requires the introduction of a correction term in the panel regression model to correct for this bias as suggested by Heckman (43), and will be further discussed in Section 3.3.2. The Probit model used to estimate the correction term for the incidental truncation is presented in Section 3.3.2.

It should be expected that overlay cracking increases with time and the change of the percentage of cracking is positive, unless some maintenance activity was performed. Several observations were found in the WSDOT data where the change in the percentage of cracking is negative, which suggests either a non-recorded routine maintenance or more likely a measurement error. Given that the dependent variable is the change of crack progression with no routine maintenance or measurement errors, left censoring (at zero) has been imposed on the observations with negative change in the percentage of alligator cracking. Regression data with censored observations are estimated using the Tobit model, which is discussed in Section 3.3.4.

Section 3.3 presents a review of the statistical approach used. Section 3.4 presents the development of the progression model. In Section 3.5 the correction term for the incidental truncation is estimated, and in Section 3.6 the final progression model is presented and the results are discussed.

3.3 Statistical Review

3.3.1 Panel Data Models

A panel, or longitudinal, data set is one that follows a given sample of individuals over time, and thus provides multiple observations on each individual in the sample.

There are several possible specifications for panel data depending on the nature of the data analyzed. Models can be fixed-effect or random-effect models depending on the specification of the term that accounts for cross-sectional heterogeneity.

A panel data regression is written as:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + u_{it}, \qquad i = 1,\ldots,n;\ t = 1,\ldots,T \qquad \textbf{(1)}$$

where i refers to the cross-sectional units or individuals,
t refers to the time periods,
$\boldsymbol{\beta}$ is a vector of parameters to be estimated,
$\mathbf{x}_{it}$ is a vector of explanatory variables, and
u_{it} the disturbance term.

When differences across units can be captured as differences in the constant term, a dummy variable is introduced to allow for the effects of omitted variables that are specific to individual cross-sectional units but stay constant over time. This type of model is known as a fixed-effects model or Least Squares Dummy Variables (LSDV) model since it can be estimated using Ordinary Least Squares (OLS) techniques by multiplying the constant term by dummy variables indicating the *i*th unit. These models can be written as:

$$y_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + u_{it} = D_i\alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + u_{it} \qquad i = 1,...,n;\ t = 1,...,T \qquad \textbf{(2)}$$

where α_i is a scalar constant representing those variables peculiar to the *i*th individual and constant in time, and

D_i is a dummy variable indicating the *i*th individual.

The fixed effects specification suffers from an obvious shortcoming in that it requires the estimation of many parameters (mainly the dummy variables) with the associated loss of the degrees of freedom. This can be avoided by introducing the random effects model. Unlike the fixed effect model where inference is conditional on the particular cross-sectional units sampled, the random-effects model is an appropriate specification if *n* cross-sectional units are randomly drawn from a large population. This is reflected in the formulation of the disturbance term

$$u_{it} = u_i + v_{it}, \qquad i = 1,...,n;\ t = 1,...,T \qquad \textbf{(3)}$$

where u_i is the random disturbance characterizing the *i*th observation and is constant in time, and v_{it} are random disturbances.

By rewriting Equation (1) using Equation (3), the random-effects model is given by:

$$y_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + u_i + v_{it}, \quad i = 1,...,n;\ t = 1,...,T \qquad \textbf{(4)}$$

The parameters $\boldsymbol{\beta}$ of the random effects are estimated using the Generalized Least Squares (GLS) technique.

3.3.2 Selection Bias (Incidental Truncation)

The incidental truncation problem, or selection bias, can be explained mathematically, in the following manner.

Suppose that y and z have a bivariate distribution with correlation ρ. Of interest is the distribution of y given that z exceeds a particular value. In this case, y is observed and represents the yearly change in the percentage of alligator cracking, while z is not observed (latent) and represents what can be defined as the propensity to crack. If y and z are positively correlated, it should be expected that the truncation of z should push the distribution of y to the right, resulting in overestimation of cracking. The truncated joint density of y and z is given by:

$$f(y,z|z>a)=\frac{f(y,z)}{\Pr ob(z>a)} \quad \textbf{(5)}$$

where a is the point at which the truncation of z occurs.

Let the equation that determines the latent variable z be

$$z_i=\boldsymbol{\gamma}'\mathbf{w}_i+\mu_i \quad \textbf{(6)}$$

And let the equation for yearly change in percentage of alligator cracking be

$$y_{it}=\boldsymbol{\beta}'\mathbf{x}_{it}+u_{it} \quad \textbf{(7)}$$

where y_{it} is the dependent variable of interest (change in the percentage of alligator cracking),
z_i is the latent variable (representing the propensity of a pavement section to crack),
$\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of parameters to be estimated,
$\mathbf{w}_i$ and $\mathbf{x}_{it}$ are vectors of explanatory variables, u_{it} and
μ_i are error terms.

y_{it} is only observed for those sections that have cracked. Since z_i represents the propensity to crack, then a section i has cracked only if z_i exceeds a certain threshold a. Without loss of generality let $a=0$, then y_{it} is observed only when $z_i>0$.

Define σ_u and σ_μ as the standard deviation of u_{it} and μ_i respectively. If μ_i and u_{it} are assumed to have a bivariate normal distribution with zero means and correlation ρ, then:

$$E[y_{it}\,|\,y_{it}\,\textit{is observed}]=E[y_{it}|z_i>0]=\boldsymbol{\beta}'\mathbf{x}_{it}+\beta_\lambda\lambda_i(\alpha_\mu) \quad \textbf{(8)}$$

So

$$y_{it} \left| z_i > 0 = \boldsymbol{\beta}' \mathbf{x}_{it} + \beta_\lambda \lambda_i(\alpha_\mu) + \eta_{it} \right. \quad \textbf{(9)}$$

where

$$\alpha_\mu = \frac{-\boldsymbol{\gamma}' \mathbf{w}_i}{\sigma_\mu} \quad \textbf{(10)}$$

and

$$\lambda_i(\alpha_\mu) = \frac{\phi(\boldsymbol{\gamma}' \mathbf{w}_i / \sigma_\mu)}{\Phi(\boldsymbol{\gamma}' \mathbf{w}_i / \sigma_\mu)} \quad \textbf{(11)}$$

where $\phi(.)$ is the standard normal distribution, and $\Phi(.)$ is the standard cumulative normal distribution, and η_{it} is a random error term.

Thus, the panel data model with incidental truncation occurring on the distribution of the cross-sectional observations is given by Equation (9). The parameters **β,** $\beta_{\lambda,}$ **γ,** and λ_i of the sample selection model are estimated using the two-step Heckman's procedure:

In the first step, the Probit Equation (11) is estimated by maximum likelihood to obtain estimates of $\boldsymbol{\gamma}$. Binary Probit models are further explained in Section 3.3.3. Then for each observation in the selected sample the following is computed:

$$\hat{\lambda}_i = \frac{\phi(\hat{\boldsymbol{\gamma}}' \mathbf{w}_i)}{\Phi(\hat{\boldsymbol{\gamma}}' \mathbf{w}_i)} \quad \textbf{(12)}$$

where $\hat{\lambda}_i$ and $\hat{\gamma}$ are the estimated values of λ_i and $\boldsymbol{\gamma}$ respectively.

In the second step of Heckman's procedure, the parameters **β** and β_λ of Equation (9) are estimated by regressing the dependent variable y_{it} on $\hat{\lambda}_i$ and the vector of explanatory variables $\mathbf{x}_{it}$.

3.3.3 Binary Probit Model

A binary choice model is a model that considers two discrete outcomes in contrast to multinomial models that consider three or more discrete outcomes. The distinction between binary models and multinomial models is important since the derivation between the two can vary significantly, especially for the Probit models. Probit models arise when the disturbance terms ε in the equation: $P_n(i) = P(\boldsymbol{\beta}_i \mathbf{x}_{in} - \boldsymbol{\beta}_I \mathbf{x}_{In} \geq \varepsilon_{In} - \varepsilon_{in}) \;\; \forall \;\; I \neq i$ are assumed to be normally distributed. An attractive feature of normally distributed variates is that the addition or subtraction of two normal variates also produces a normally distributed variate.

Of interest for this project is the probability that the latent variable z of Equation (6) is positive. Therefore, Cr can be defined as an indicator that section i has cracked or not, and the binary outcomes can be defined as 0 and 1, where $Cr = 1$ indicates that the section has cracked and $Cr = 0$ indicates that the section did not crack. Then

$$Cr = 0 \qquad \text{If } z \leq 0 \tag{13}$$

$$Cr = 1 \qquad \text{If } z > 0 \tag{14}$$

Under the above assumptions, Equation (4) can be rewritten to give the following Probit model:

$$P_i(Cr = 1) = \Phi(\boldsymbol{\gamma}'\mathbf{w}_i) \tag{15}$$

and

$$P_i(Cr = 0) = 1 - \Phi(\boldsymbol{\gamma}'\mathbf{w}_i) \tag{16}$$

where $P_i(Cr = 1)$ is the probability of choosing the outcome $Cr = 1$ over the outcome $Cr = 0$.

The parameter vector $\boldsymbol{\gamma}$ is estimated using the maximum likelihood method. Let δ_{in} be defined as a dummy variable that takes the value 1 if the observed discrete outcome for observation n is 1 (Cr = 1) and zero otherwise. The likelihood function is thus given by:

$$L = \prod_i [\Phi(\boldsymbol{\gamma}'\mathbf{w}_i)]^{\delta_i} [1 - \Phi(\boldsymbol{\gamma}'\mathbf{w}_i)]^{1-\delta_i} \tag{17}$$

The log likelihood function is given by

$$LL = \sum_i [\delta_i LN\Phi(\boldsymbol{\gamma}'\mathbf{w}_i) + (1-\delta_i)LN(1-\Phi(\boldsymbol{\gamma}'\mathbf{w}_i))] \quad \textbf{(18)}$$

where LN is the natural log function.

3.3.4 Censored Panel Data and Tobit Models

The regression model for a censored dependent variable with a normal distribution is referred to as the Tobit model. Let y_{it}^* be a latent variable with an uncensored normal distribution where:

$$y_{it}^* = \boldsymbol{\beta}'\mathbf{x}_{it} + \beta_\lambda \lambda_i(\alpha_\mu) + \eta_{it} = \boldsymbol{\beta}'\mathbf{x}_{it} + \beta_\lambda \lambda_i(\alpha_\mu) + \eta_i + \theta_{it}, \quad i = 1,...,n;\ t = 1,...,T \quad \textbf{(19)}$$

where

$$\eta_{it} = \eta_i + \theta_{it} \quad \textbf{(20)}$$

η_i is the random disturbance characterizing the *i*th observation and is constant in time, and

θ_{it} are random disturbances. Equation (19) is similar to Equation (4) and indicates that Equation (19) is a random effects panel data model.

And let

$$y_{it} = 0 \qquad \text{if } y_{it}^* \le 0, \quad \textbf{(21)}$$

$$y_{it} = y_{it}^* \qquad \text{if } y_{it}^* > 0 \quad \textbf{(22)}$$

where $\boldsymbol{\beta}$ is a vector of parameters to be estimated,
$\mathbf{x}_{it}$ is a vector of explanatory variables, and
β_λ is the coefficient of the incidental truncation term $\lambda_i(\alpha_\mu)$.

The parameters $\boldsymbol{\beta}$ and β_λ are estimated using the maximum likelihood technique where, under the assumption that η_i is randomly distributed with density function $g(\eta)$, the likelihood function of the censored data takes the form (44):

$$L = \prod_{i=1}^{N} \int \left[\prod_{t \in c_i} F(-\boldsymbol{\beta}'\mathbf{x}_{it} - \beta_\lambda \lambda_i(\alpha_\mu) - \eta_i) \prod_{t \in \bar{c}_i} f(y_{it} - \eta_i - \boldsymbol{\beta}'\mathbf{x}_{it} - \beta_\lambda \lambda_i(\alpha_\mu)) \right] g(\eta_i) d\eta_i \quad \textbf{(23)}$$

where $c_i = \{t | y_{it} = 0\}$, $\bar{c}_i$ denotes its complement,
$f(.)$ denotes the density function of θ_{it} and
$F(a) = \int_{-\infty}^{a} f(\theta) d\theta$.

Once the parameters $\boldsymbol{\beta}$ and β_λ of Equation (23) are estimated, then the expected value of the latent variable function is given by

$$E[y_{it}^{*}|\mathbf{x}_{it}] = \boldsymbol{\beta}'\mathbf{x}_{it} \qquad \textbf{(24)}$$

Note that the term $\beta_\lambda \lambda_i(\alpha_\mu)$ is only included to obtain unbiased estimates of $\boldsymbol{\beta}$. Once $\boldsymbol{\beta}$ are estimated, the term $\beta_\lambda \lambda_i(\alpha_\mu)$ is not used for prediction purposes. Equation (24) can be used for predicting y_{it} for a sample of observations that is selected and known to be uncensored. However, for an observation randomly drawn from the population, which may or may not be censored, the expected value of the dependent variable of interest y_{it} is

$$E[y_{it}|\mathbf{x}_{it}] = \Phi\left(\frac{\boldsymbol{\beta}'\mathbf{x}_{it}}{\sigma}\right)\left(\boldsymbol{\beta}'\mathbf{x}_{it} + \sigma\psi_{it}\right) \qquad \textbf{(25)}$$

where

$$\psi_{it} = \frac{\phi(\boldsymbol{\beta}'\mathbf{x}_{it}/\sigma)}{\Phi(\boldsymbol{\beta}'\mathbf{x}_{it}/\sigma)} \qquad \textbf{(26)}$$

and σ is the standard deviation of the error terms v_{it},
$\phi(.)$ is the standard normal distribution, and
$\Phi(.)$ is the standard cumulative normal distribution.

3.4 Data Description

3.4.1 Sample Selection for the Progression Model

The propagation, or progression, of overlay cracking starts only after crack initiation has occurred in the overlay. This is why crack progression models are used for prediction purposes only after an initiation model has predicted a failure in a pavement section. Thus, in order to have consistency between the crack initiation and the crack progression models, the pavement sections used for the estimation of the progression model should be selected from the sample of pavement sections used for the estimation of the initiation model. Optimally, one would want to select all the pavement sections used for the estimation of the initiation model to estimate the progression model; however since some pavement sections did not fail according to the crack initiation criteria (5 Percent of the Wheelpath Cracked for this study), they can not be included in the sample used for the estimation of alligator cracking progression, resulting in the problem of incidental truncation discussed in Section 3.3.2.

The sample used for the estimation of the progression model was selected from the Washington State PMS database. The sample used for the estimation of the crack initiation model consists of 7,162 pavement sections, of which 5,441 are complete observations, i.e., where cracking has initiated in the overlay, and the rest are right censored, i.e., crack initiation has not occurred by the year of the last condition survey. Given that alligator crack progression is conditional on crack initiation, only the pavement sections treated as complete observations for the initiation model should be selected, and alligator crack progression should be observed for each of those sections from the year that cracking initiated to the last year of the condition survey. The selected sample thus consists of 5,441 pavement sections observed from Year 1 to Year 12 for each different section, and constitutes a panel data set with 36,194 observations. Table 1 below shows the summary statistics of the sample.

Table 1: Summary Statistics of the Sample

Total number of observations	36,194
Number of pavement sections	5,441
Minimum number of observations (years) per section	1
Average number of observations (years) per section	6.7
Maximum number of observations (years) per section	12

3.4.2 Description of Relevant Variables

Some additional variables relevant to the progression model were created and are described below:

- Y_{it}: Percentage of the wheelpaths with alligator cracking in pavement section *i* at time *t,* where *t* is the number of years since the last overlay was built. The progression model predicts the change in the percentage of alligator cracking in a pavement section *i* as a function of time. Alligator cracking is defined as the equivalent of Type B and Type C (combined extent of the two types) in the Caltrans PMS.
- $Y_{i(t-1)}$: Percentage of alligator cracking in pavement section *i* at time (*t*-1).This variable captures the effect of conditions in the previous year on the change of the percentage of alligator cracking in a pavement section *i* at year *t*.
- Δ_{it}: Represents the yearly change in the percentage of alligator cracking for pavement section *i* between time *t* and (*t*-1) and is given by:

$$\Delta_{it} = Y_{it} - Y_{i(t-1)} \qquad \textbf{(27)}$$

Since the progression of alligator cracking is the dependent variable, in terms of the percentage of the wheelpaths with alligator cracking, Δ_{it} could have been chosen as the dependent variable for the progression model. However, there are several incidences in the data where Y_{it} is smaller than $Y_{i(t-1)}$, resulting in a decrease of the percentage of alligator cracking and a negative Δ_{it}. A negative Δ_{it} can be explained by the occurrence of a nonrecorded routine maintenance activity, or a measurement error. The desired model is for the change of crack progression with no routine maintenance or measurement errors. Therefore left censoring was imposed on the observations with negative change in the percentage of alligator cracking, and the following variable was created:

- Cens_Δ_{it}: which is the progression model dependent variable and represents the left-censored yearly change in the percentage of alligator cracking for pavement section *i* between time *t* and (*t*-1). It is defined as:

$$Cens\_\Delta_{it} = \Delta_{it} \qquad If\ \Delta_{it} \geq 0 \tag{28}$$

$$Cens\_\Delta_{it} = 0 \qquad If\ \Delta_{it} < 0 \tag{29}$$

Note that Δ_{it} and Cens_Δ_{it} correspond to, respectively, y_{it}^* and y_{it} discussed in Section 3.3.4.

- E_Alli$_i$: Existing alligator cracking before rehabilitation. This variable represents the last measured cracking before the last rehabilitation activity was performed. It represents the distress level of the pavement before the overlay. This is an important variable in modeling overlay cracking because overlay cracking is partly due to reflection cracking, which occurs when there are cracks in the previous pavement surface layer and they propagate through the overlay.

- ULT$_i$: Sum of the thickness of the underlying asphalt concrete pavement layers (in ft.).

- Untrthick$_i$: The thickness of the nontreated base (in ft.)

- Actbthick$_i$: The thickness of asphalt concrete-treated base (in ft.)

- Pctbthick$_i$: The thickness of portland cement-treated base (in ft.)

- Traffic$_{it}$: Traffic in ESALs for pavement section *i* at time *t*. This variable reflects the yearly traffic loading in ESALs. Traffic$_{it}$ is the number of ESALs at section *i* at year t_0+t, where t_0 is the year the overlay was built and *t* the number of years since the overlay was built. Traffic$_{it}$ varies across different pavement sections, and usually increases with time for any given section *i*.

- $Mintempc_{it}$: Average monthly minimum temperature of the coldest month (December) in ^{o}C. $Mintempc_{it}$ is the average minimum temperature of the coldest month for section *i* in year t_0+t. Thus $Mintempc_{it}$ varies across pavement sections and over time for the same pavement section. The increase in the percentage of alligator cracking between times (t-1) and t is dependent on the climate conditions at time t, while past climate conditions affect this increase through the lagged variable $Y_{i(t-1)}$ as will be discussed in Section 3.6.
- $Precip_{it}$: Annual precipitation (in mm): the annual precipitation for section *i* in year t_0+t.
- Pr_aa, Pr_ba: The probability of choosing overlay material types AA or BA respectively. These represent WSDOT asphalt concrete mix Types A and B, respectively. WSDOT Type A mix is similar to Caltrans Type A mix. WSDOT Type B mix has quality requirements that are between those of Caltrans Type A and Type B mixes.
- Newoverlay1: Instrumented overlay thickness (in ft.). This variable reflects the thickness of the new overlay constructed on top of the existing pavement.
- $Overlayaa_i$: The product of Newoverlay1 and Pr_aa. Reflects the structural strength of the overlay through the interaction between the choice of material type AA and the thickness of the overlay. This variable changes across pavement sections and is time independent.
- $Overlayba_i$: The product of Newoverlay1 and Pr_ba. Reflects the structural strength of the overlay through the interaction between the choice of material type BA and the thickness of the overlay. This variable changes across pavement sections and is time independent.
- λ_i: The correction term for incidental truncation. This variable corrects for the selection bias. A theoretical discussion of λ_i was presented in Section 3.3.2; Section 3.5 presents the estimation of this correction term.

An important detail in the WSDOT traffic data was the lane distribution of ESALs. The lane distribution factor was not included in the original model and this omission resulted in an underestimation of ESALs in the design lane that carries most of the traffic. However, both the revised crack initiation and crack progression models were updated using the correct distribution factor.

3.5 Estimation of the Incidental Truncation Correction Term

As discussed in Section 3.4.1, the sections that have crack initiation were used to estimate the progression model. This introduces a selection bias that needs to be corrected for, by using Heckman's procedure, which was presented in Section 3.3.2. The first step of Heckman's procedure using a Probit model (discussed is Section 3.3.3) to estimate the parameters $\boldsymbol{\gamma}$ of Equation (18) using the maximum likelihood method is presented in this section of the report. Once $\boldsymbol{\gamma}$ are estimated, Equation (12) is used to compute $\hat{\lambda}_i$.

Define the latent variable explaining the propensity to crack z_i of Equation (6) as:

$$z_i = \gamma_0 + \gamma_1 Actbthick + \gamma_2 Pctbthick + \gamma_3 Untrthick + \gamma_4 ULT + \gamma_5 Pr\_aa + \gamma_6 Pr\_ba + \gamma_7 Cum\_ESAL + \gamma_8 FTprep + \gamma_9 Newoverlay1 \quad \textbf{(30)}$$

Then the Probit model of Equation (15) is specified as follows:

$$Pr(Cr=1) = \Phi(\gamma_0 + \gamma_1 Actbthick + \gamma_2 Pctbthick + \gamma_3 Untrthick + \gamma_4 ULT + \gamma_5 Pr\_aa + \gamma_6 Pr\_ba + \gamma_7 Cum\_ESAL + \gamma_8 FTprep + \gamma_9 Newoverlay1) \quad \textbf{(31)}$$

Where γ_0 to γ_9 are parameters to be estimated, and Actbthick, Pctbthick, Untrthick, ULT, Pr_aa, Pr_ba, Cum_ESAL, FTprep, and Newoverlay1 are explanatory variables for the crack initiation model. The definitions of these explanatory variables were presented in report UCPRC-RR-2005-5 (5).

The same sample that was used for the estimation of the initiation model was used to estimate the Probit model of Equation (31). Table 2 presents the results of the Probit model estimation.

All the explanatory variables of Table 2 are significant to the 10% significance level. Greater thicknesses of the structural variables reduce the probability of crack initiation. The structural variables are the thicknesses of the asphalt concrete-treated base, the portland cement-treated base, the untreated base, the thickness of previous asphalt concrete layers, and the thickness of the overlay. Overlay thickness has by far the largest effect in reducing the probability of cracking, as one would expect. A treated base results in a lower probability of cracking than an untreated base of the same thickness. An asphalt concrete-treated base has a larger effect than a portland cement-treated base. Material type AA also appears more effective than material type BA in reducing the probability of cracking. Table 2 also shows that the greater the cumulative ESALs, and the harsher the climate conditions (higher FTprep, which is the product of freeze-thaw cycles and annual rainfall), the larger the probability of cracking for a pavement section.

When analyzing the results of the Probit model above, one has to be careful about interpreting the meaning of the probability of cracking for a pavement section defined in this section, and to differentiate that from the probability of cracking initiation. The probability of cracking defined in this section represents a binary output that a pavement section has cracked or not at a given time (or at a given Cumulative ESALs). Thus the specification of the Probit model does not account for the history of a pavement section prior to failure, and does not benefit from the additional information that the pavement sections in the considered sample did not fail in previous years.

The duration model takes into account this additional information through the definition of the hazard rate as the probability that a section *i* fails at a certain time *t* (or Cumulative ESALs) *given it has survived until t.* Moreover, the Probit model is a point estimate of the probability of failure of a section *i* at a time *t*, while the duration model estimates the *distribution* of the probability of failure of a section *i* versus time. This is why duration models are richer, and more appropriate to use for predicting the life, or time to failure, of a pavement section *i*, while the Probit model above is used mainly for estimating the correction term for the incidental truncation, rather than for predicting the life of overlays. The use of a Probit model instead of a duration model in Heckman's procedure results from the normality assumption on the distribution of the error terms of z_i and y_{it} in Equations (6) and (7).

The estimated parameters $\boldsymbol{\gamma}$ of the Probit model in Equation (35) are then used to compute the incidental truncation correction term λ_i. This completes the first step of Heckman's procedure. The second step consists of introducing λ_i as an explanatory variable during the estimation of y_{it} and is performed in Section 3.6.

Table 2: Results of the Probit Model for Probability that a Section Cracks, Pr(Cr=1)

Pr(Cr=1)		
Variable	**Coefficient**	**t-statistics**
Constant	6.64E+00	9.55
Actbthick (thickness of asphalt-treated base, ft)	-1.60E+00	-6.49
Pctbthick (thickness of portland cement-treated base, ft)	-7.95E-01	-6.26
Untrthick (thickness of untreated base, ft)	-5.44E-01	-11.28
ULT (thickness of underlying asphalt concrete, ft)	-9.00E-01	-10.96
Pr_aa (Type A asphalt concrete used)	-4.25E+00	-5.26
Pr_ba (Type B asphalt concrete used)	-9.99E-01	-1.87
Cum_ESAL (cumulative Equivalent Single Axle Loads)	2.47E-06	29.28
FTprep (product of annual freeze-thaw cycles and annual precipitation)	1.22E-05	4.64
Newoverlay1 (thickness of overlay, ft)	-4.02E+01	-15.95

Goodness of Fit Measures		
Number of Observations	Likelihood Ratio	Pseudo R2
7,162	1,149.5	0.153

3.6 The Crack Progression Model

3.6.1 Model Specification

In order to estimate the crack progression model, a sample of 36,194 observations, described in Section 3.4.1, was used. A panel data Tobit model was selected, and the dependent variable, $Cens\_\Delta_{it}$ described in Section 3.4.2, was regressed on explanatory variables, using the following model specification:

$$Cens\_\Delta_{it} = \beta_0 + \beta_1 Y_{i(t-1)} + \beta_2 E\_Alli_i + \beta_3\ actbthick_i + \beta_4\ pctbthick_i + \beta_5\ untrthick_i + \beta_6 ULT_i + \beta_7 Overlayaa_i + \beta_8 Overlayba_i + \beta_9 Traffic_{it} + \beta_{10} Precip_{it} + \beta_{11} Mintempc_{it} + \beta_\lambda \lambda_i \quad \mathbf{(32)}$$

The variables $Y_{i(t-1)}$, $Overlayaa_i$, $Overlayba_i$, $Traffic_{it}$, $Precip_{it}$, $Mintempc_{it}$, and λ_i were defined in Section 3.4.2. The subscript *i* indicates that an explanatory variable changes across pavement sections, and the subscript *t* [and (*t-1*)] indicates that an explanatory variable changes in time. If both subscripts *i* and *t* are present, then the explanatory variable changes both across pavement sections and in time.

3.6.2 Expectations of the Model Results

The expected effects of the explanatory variables on the progression of alligator cracking are described in this section. It is important to define the expected effects of the explanatory variables prior to regression to apply appropriate engineering judgment to the statistical modeling results.

A major limitation of the Washington State PMS data is that alligator cracking rarely exceeds 10 percent, because WSDOT essentially follows a pavement preservation approach and a new overlay is usually put in place before cracking exceeds 10 percent of the wheelpath with alligator cracking. Thus the model parameters reflect a network and its performance data in which overlays are placed before there is less than 10 percent alligator cracking in the wheelpath, and the overlays are overlaid again before they have more than 10 percent of the wheelpath with alligator cracking. The overwhelming majority of the overlays are also what would be defined by Caltrans as “maintenance overlays” with typical thicknesses of about 0.15 ft (45 mm). For thin overlays on cracked pavements it would be expected that reflection cracking would be the mechanism of failure in the overlay, with the cracks in the existing pavement reflecting up through the overlay. However, because the extent of existing cracking is very low, it would be expected that the extent of reflection cracking in the overlay would asymptote to the extent of existing cracking in underlying pavement, always less than 10 percent. This would be true for the WSDOT data set. After some period of time with the reflection cracking mechanism completed and cracking remaining at the asymptote of the previous existing cracking extent, it would be expected that bottom-up fatigue cracking would propagate through the underlying existing asphalt layers and through the overlay, resulting in an acceleration of cracking extent from that time on.

If Caltrans is not using a similar pavement preservation strategy as WSDOT, and is instead placing overlays only at greater extents of alligator cracking, then the model parameters will need to be recalibrated using Caltrans performance data.

It is expected that a stronger structure will have high resistance to cracking and will reduce the rate of progression of alligator cracking. Accordingly, an increase in the thickness of the overlay, both for material types AA and BA, an increase in the thickness of the untreated or treated base, and an increase in the thickness of underlying asphalt concrete layers, are expected to decrease the rate of alligator cracking progression by increasing the strength of the pavement.

On the other hand, an increase in the existing cracking before rehabilitation is expected to increase the rate of crack progression because the cracking results in a weaker pavement structure and because of the mechanism of propagation by reflection cracking to the overlay surface. It is also expected that as the minimum temperature increases, the stiffness of the asphalt concrete overlay decreases, which decreases the rate of alligator cracking progression. Precipitation is expected to accelerate the rate of cracking since water infiltrates to the granular layers and the subgrade and softens them, thus weakening support for the asphalt layers and rendering them more susceptible to cracking. Greater precipitation would also be expected to increase the cracking susceptibility of the overlay.

3.6.3 Model Results and Their Interpretations

Table 3 shows the results of the estimation of the parameters of Equation (32). The results shown in Table 3 confirm the expectations in terms of the correctness of the signs. Furthermore, the t-statistics show that each variable is a significant explanatory variable of the progression of alligator cracking at the five percent significance level.

Table 3: Results of the Tobit Model Regression

Variable	Variable Description	Coefficient	t-statistics
Constant		1.18E+00	3.39
$Y_{i(t-1)}$	Percent of wheelpath w/ alligator cracking	-5.86E-01	-39.1
E_Alli_i	Percent wheelpath w/crack before overlay	8.07E-02	20.01
$Actbthick_i$	Thickness of asphalt-treated base, ft	-0.175E+00	-4.89
$Pctbthick_i$	Thickness of PCC-treated base, ft	-0.171E+00	-8.91
$Untrthick_i$	Thickness of untreated base, ft	-0.357E-01	-5.09
ULT_i	Thickness of underlying AC, ft	-1.26E+00	-8.77
$Overlayaa_i$	Thickness of overlay with Type A mix, ft	-3.88E+00	-4.32
$Overlayba_i$	Thickness of overlay with Type B mix, ft	-1.54E+00	-6.56
$Traffic_{it}$	Annual ESALs	4.56E-06	5.45
$Precip_{it}$	Annual rainfall, mm	4.40E-04	10.18
$Mintempc_{it}$	Average min daily temp in December, °C	-5.42E-02	-5.74
λ_i	Incidental truncation correction term	1.20E+00	15.97

Error term	Value	t-statistics
sigma_u	0.84	14.7
sigma_e	4.41	230.79
Rho	0.035	N/A

Number of Observations	Wald Test
36,194	2,230.52

The signs of the explanatory variables indicate the following effects on the rate of crack progression:

- The value for β_1 indicates that the greater the amount of alligator cracking in the overlay, the smaller the increase in alligator cracking, which means that the cracking progression trend is concave in time. This is a surprising result, as there is no reason to expect the amount of cracking to level off at a particular value. The explanation for this behavior is that the data used for development of this model comes from in-service pavements. As such, these overlays were subjected to (unrecorded) maintenance activities, possibly including crack sealing or patching. As noted in Section 3.4.2, for some observations, the value of Δ_{it} was negative, which is why Tobit (censored) regression was used as an estimation method. Censoring replaces these negative values with zeros. The effect of these zero values for Δ_{it} is to force a leveling off of alligator cracking. Therefore, this model predicts cracking progression in overlays *that are subject to maintenance activities.* The implication of this result is that the model should only be used to predict cracking progression for agencies that follow a similar maintenance policy.

- The value for β_2 indicates that the greater the existing alligator cracking in previous layers, the faster the progression of alligator cracking in the overlay, confirming the hypothesis that overlay cracking is mostly due to reflection cracking.
- A thicker underlying structure (base thickness, previous AC layers thickness, overlay thickness) results in a smaller rate of crack progression. HMA- or PC-treated bases do not seem to differ much in reducing the rate of crack progression, however they are both significantly better (almost by a multiple of 5) in resisting crack progression than untreated bases of the same thickness. The underlying AC layer is about 10 times more effective in resisting crack progression than even the strongest base of the same thickness.
- Overlay thickness appears to have the largest effect on resisting crack progression as one would expect, with Type A overlays about more than twice as effective in reducing the rate of alligator crack progression than Type B overlays of the same thickness.
- Traffic (ESAL) appears to have a significant effect on the rate of progression of alligator cracking; the higher the traffic at a given year the larger the rate of crack progression.
- Climate variables, particularly yearly precipitation and minimum temperature, also play a significant role: the higher the yearly precipitation, the higher the rate of crack progression, while higher minimum temperatures reduce the rate of crack progression.
- The coefficient β_λ is significant suggesting that the correction for the incidental truncation is appropriate. Moreover, since $\beta_\lambda > 0$, this indicates that $\boldsymbol{\beta}'\mathbf{x}$ is reduced when the incidental truncation correction term is included compared to a regression with no incidental truncation correction term, which means that the rate of increase of alligator cracking is reduced when the correction term is introduced in the regression. This result is expected since the correction term corrects for the over-representation of weaker pavement overlays in the sample.

The values and significance of sigma_u, sigma_e, and rho require discussion. Sigma_u represents the standard deviation of the random disturbance η_i, discussed in Equation (19), characterizing the *i*th observation and accounting for cross-sectional heterogeneity in a random effect panel data model. Sigma_e represents the standard deviation of the random disturbances θ_{it} in Equation (19), and accounts for random error terms in time and across sections. Rho represents the portion of the total error term that is due to unobserved heterogeneity and to random error, and is given by:

$$Rho = \frac{(sigma\_u)^2}{(sigma\_u)^2 + (sigma\_e)^2} \qquad \textbf{(33)}$$

The model coefficients of Equation (32) were estimated using a random-effects model; however the very low value of Rho (0.035, which is almost zero) suggests that unobserved heterogeneity is nonexistent in the model. This can be explained by the fact that the incidental truncation correction terms, which only vary across cross-sectional observations, act as dummy variables for the different pavement sections. This is equivalent to a fixed effect model specification as discussed in Section 3.3.1. This model differs slightly from a fixed effect panel data model since some, but only a few, pavement sections can have the same correction term λ_i and thus share the same identifier, so that λ_i is not a "perfect" dummy variable.

3.6.4 Model Predictions

In this section the crack initiation and progression model suite is used to perform some predictions of the initiation and progression of alligator cracking with time. A spreadsheet was used for applying the models of crack initiation and progression. The prediction methodology and the details of the spreadsheet are described in Appendix A.

It must be emphasized that the model predicts well for explanatory variables varied within the range of its values in the data only. The model specification (variables and their relationships) works well within the ranges of data used to calibrate the model, but it must be recalibrated for data outside this range. Recalibration is essential for overlay thickness (variables Overlayaa and Overlayba in Table 3) since Washington State's maintenance strategy is to perform pavement preservation mainly with overlays averaging about 0.15 ft (45 mm) thickness, and place few thicker rehabilitation overlays. Recalibration is also essential if overlays are being placed after cracking in the existing pavement has propagated to greater extents than is the practice of WSDOT (variable E_Alli in Table 3). WSDOT almost always places overlays before cracking has exceeded 10 percent of the wheelpath cracked and typically overlays at about 5 percent of the wheelpath cracked.

If greater extents of cracking in the existing pavement, outside the range of data are used, this will lead to a severe under-prediction of the extent of cracking and the rate of crack propagation. This occurs because cracking in the overlay will reach the level of cracking in the pavement prior to overlay, for thin overlays on relatively thick existing structures because the mechanism is reflection of the existing cracks. Eventually, bottom-up fatigue cracking will occur and propagate to the surface. However, this is not encountered in this database because WSDOT continues to apply preservation overlays, slowly increasing the structural capacity of the section; this is confirmed by inspecting the histograms of alligator cracking extents in the current and previous overlays, shown in Figures 2 and 3. The increase in the structural capacity added by the overlays appears to stay ahead of the bottom-up damage development in the rest of the asphalt layers for this data set. This might not be true for greater levels of annual truck traffic (in terms of ESALs, variable Traffic in Table 3) than are encountered in the WSDOT data.

Another caveat is that this model predicts cracking progression in overlays that are subject to maintenance activities. The implication of this result is that the model should only be used to predict cracking progression for agencies that follow a similar maintenance policy.

In order to perform predictions, a typical pavement section was selected and the values of its explanatory variables were defined as "default values." Each of the explanatory variables of the typical section was varied from its 25th percentile to its median and then its 75th percentile (Table 4). The only variables that made a significant difference in the prediction of alligator cracking initiation and progression were: overlay material type (AA vs. BA) and ESAL. The predictions for different values of overlay material type and ESAL are shown in Figure 3 through Figure 10.

As is explained in Appendix A, the spreadsheet creates a graph that shows the cracking paths resulting from 1,000 simulated experiments. To show that different cracking paths have different probabilities, the graph includes information on the frequency of each path.

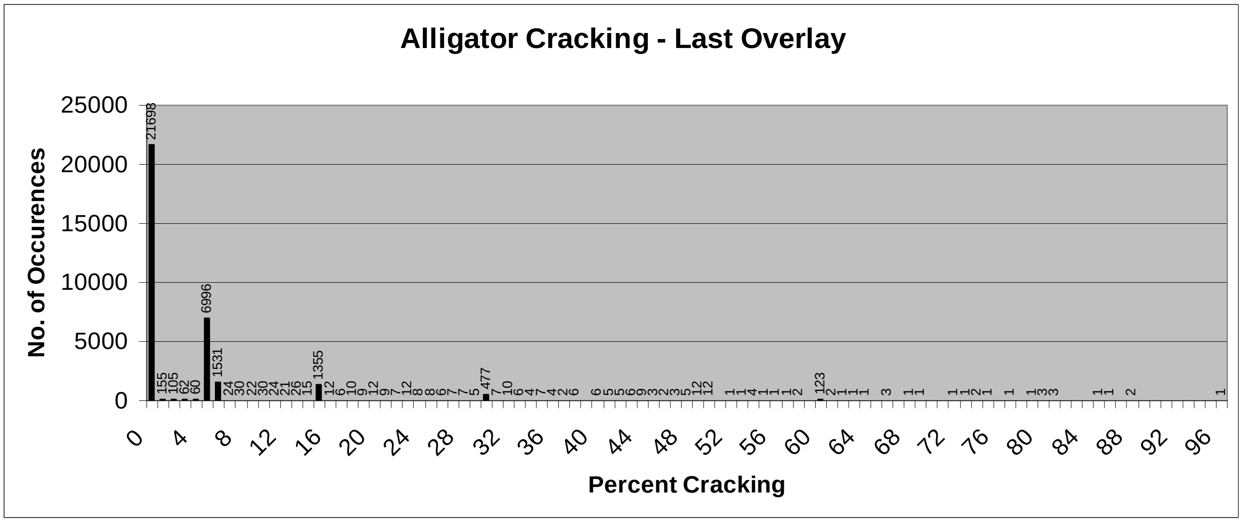

Figure 2: Histogram of percent cracking in the wheelpaths of the current overlay.

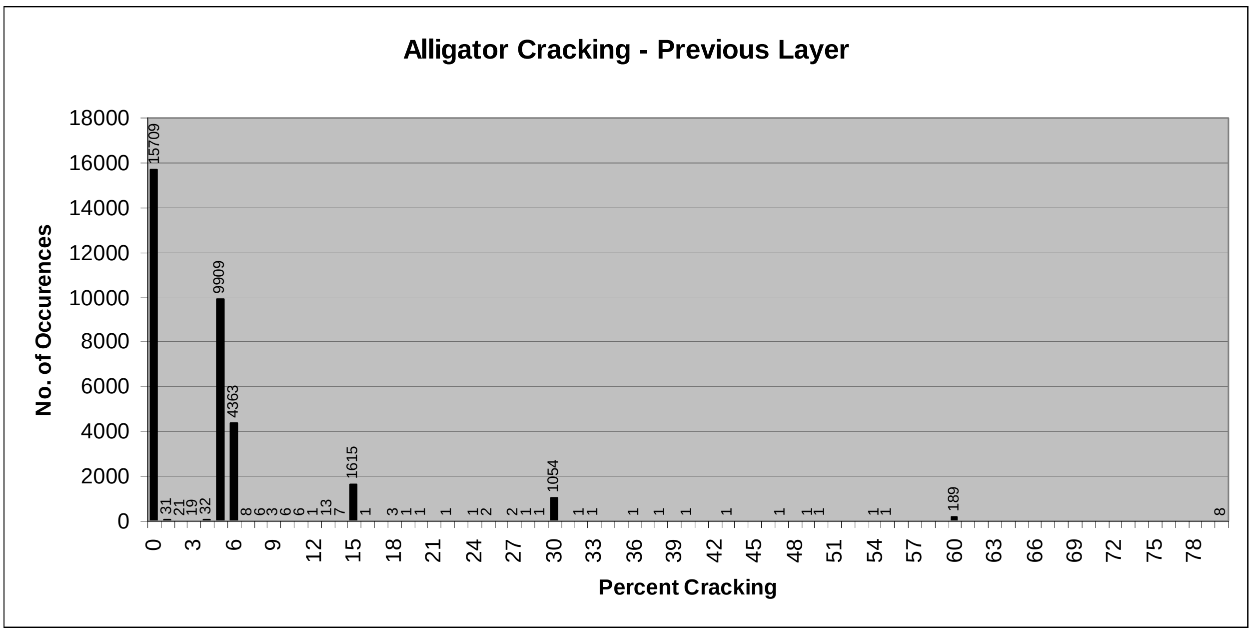

Figure 3: Histogram of percent cracking in the wheelpaths at the time of most recent overlay.

Table 4: Default Values of the Typical Section Used for Predictions for Washington State

AA						
	Allig. (%)	**Long. (%)**	**UnTrThick (in)**	**SurfThk (in)**	**PrevThk (in)**	**Tmax (F)**
median	0	30	6	1.8	7.0	78.8
lower 25%	0	0	4.6	1.8	4.7	71.6
upper 25%	5	30	10.0	1.8	9.4	86.0
	Tmin (F)	**FTCycle**	**Prep (in)**	**FTPrep**	**ACTB thick (in)**	**PCTB thick (in)**
median	33.8	20	35	700	0 (4.2 w/o others)	0 (6 w/o others)
lower 25%	23.0	11.8	15	177	0 (3.96 w/o others)	0
upper 25%	33.8	60	24.6	1476	0 (4.2 w/ others	0
BA						
	Allig. (%)	**Long. (%)**	**UnTrThick (in)**	**SurfThk (in)**	**PrevThk (in)**	**Tmax (F)**
median	5	30	8.5	1.8	4.78	78.8
lower 25%	0	30	6	1.4	3.27	71.6
upper 25%	6	30	12	1.8	6.6	86
	Tmin (F)	**FTCycle**	**Prep (in)**	**FTPrep**	**ACTB thick (in)**	**PCTB thick (in)**
median	33.8	17.7	30	531	0 (4.2 w/o others)	0
lower 25%	23	11.8	15	177	0 (3.6 w/o others)	0
upper 25%	33.8	60	24.6	1476	0 (4.5 w/o others)	0

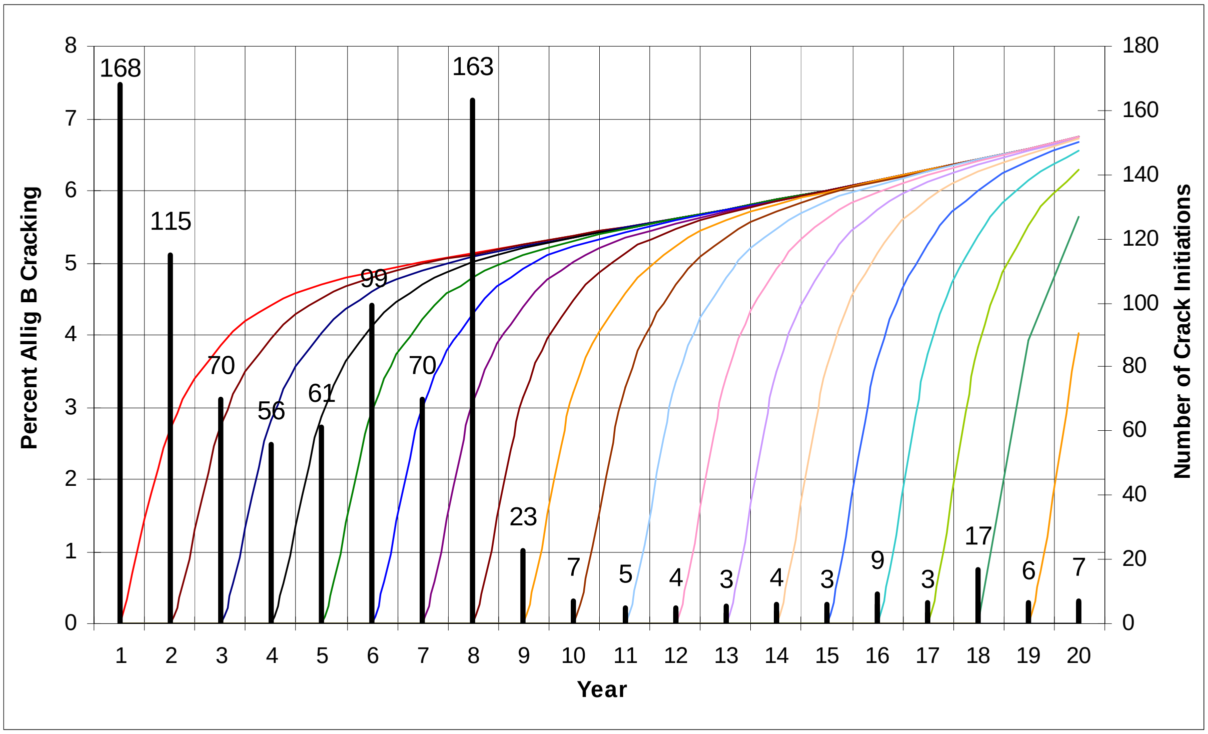

Figure 4: Overlay Type AA, all explanatory variables set at their median values, ACTB = 0, PCTB = 0, annual ESAL = 250,000 in design lane, 3% traffic growth.

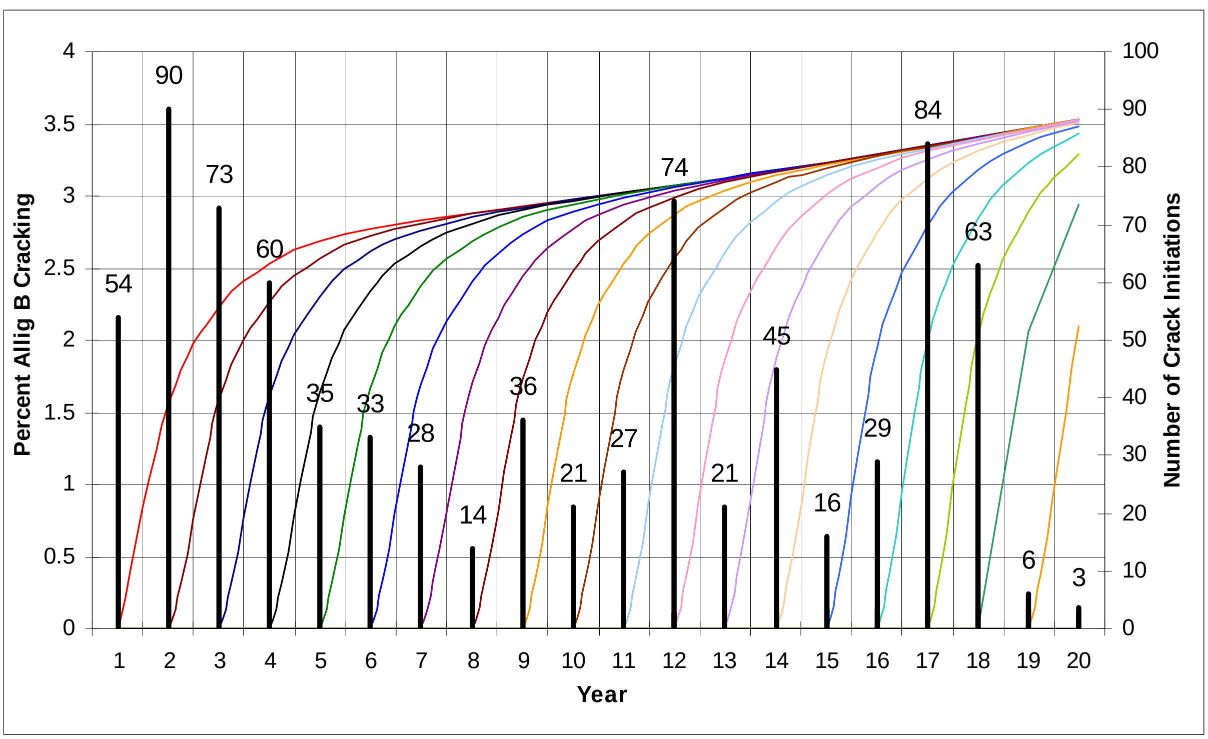

Figure 5: Overlay Type AA, all explanatory variables set at their medians, base dummy variables as in Figure 4, but ESAL = 100,000 in design lane.

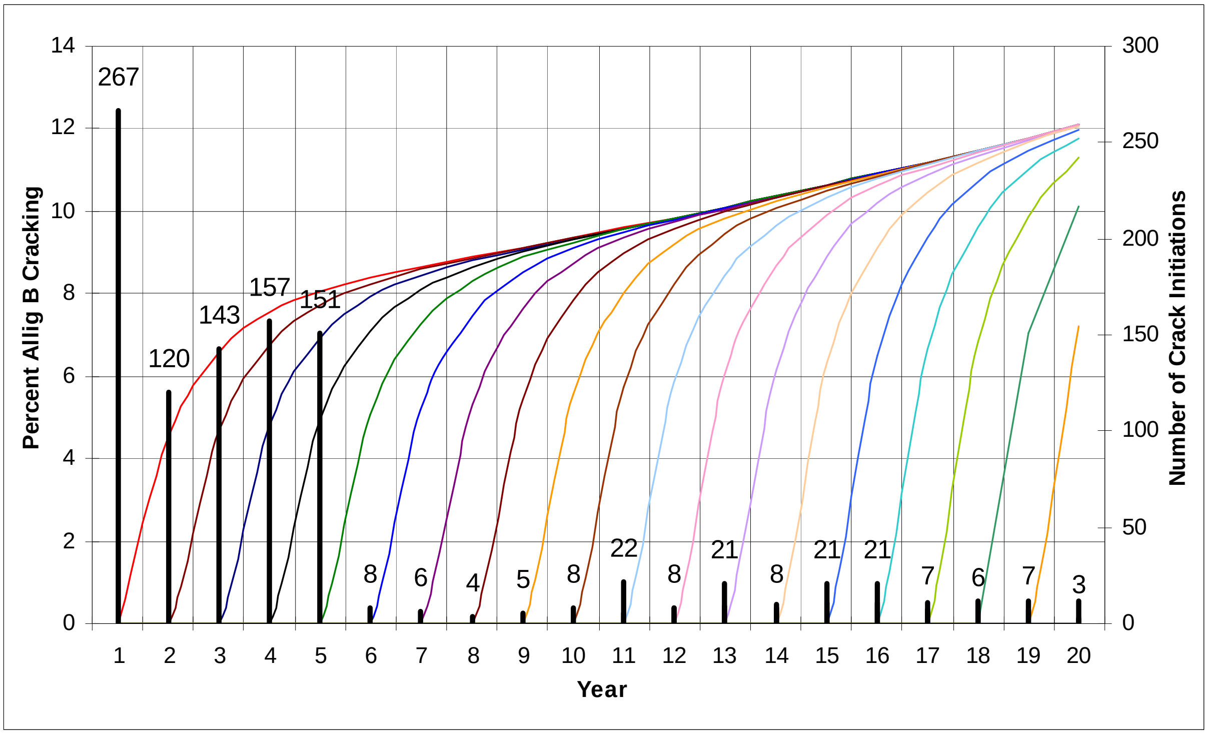

Figure 6: Overlay Type AA, all explanatory variables set at their medians, base dummy variables as in Figure 4, but annual ESAL = 500,000 in design lane.

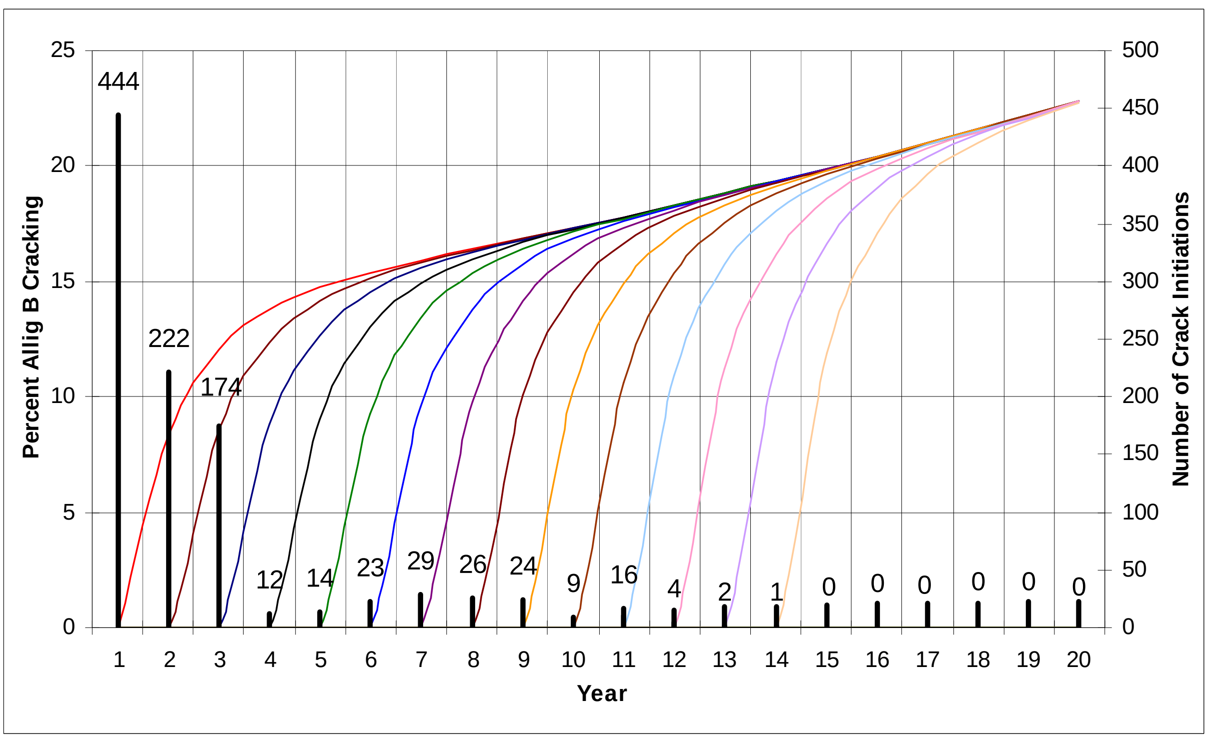

Figure 7: Overlay Type AA, all explanatory variables set at their medians, base dummy variables as in Figure 4, but annual ESAL = 1,000,000 in design lane.

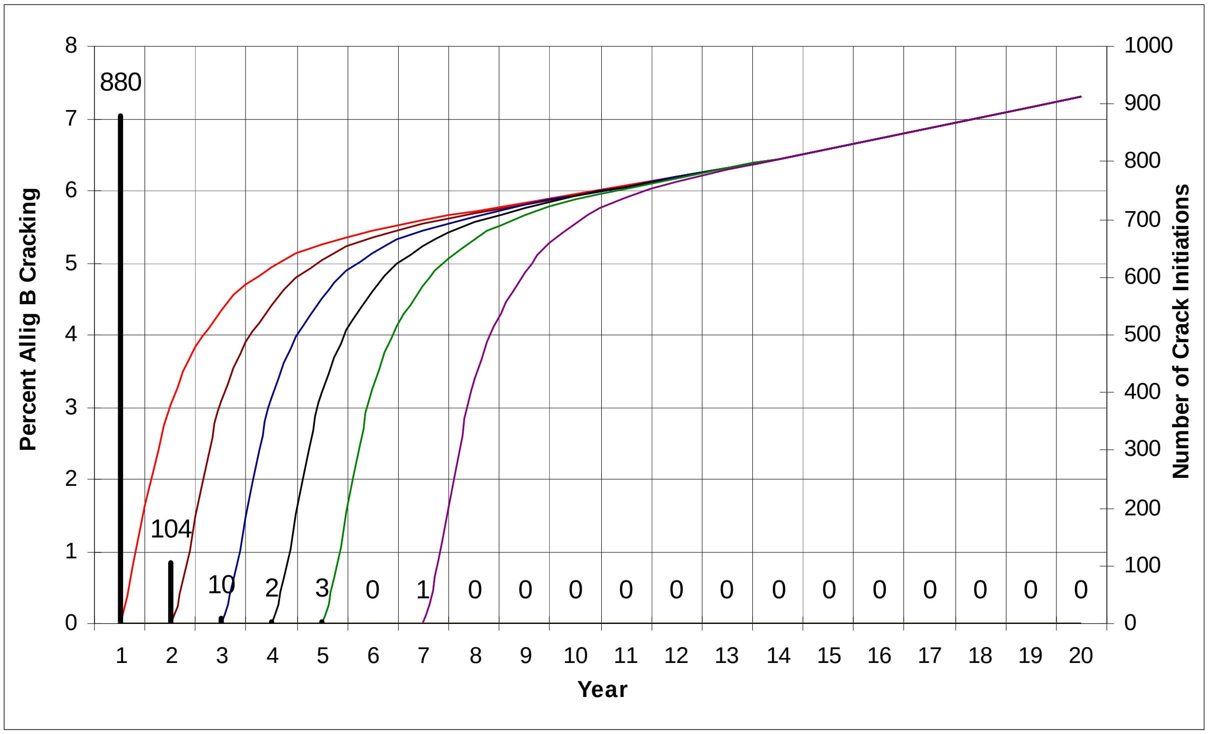

Figure 8: Overlay Type BA, all explanatory variables set at their median values, ACTB = 0, PCTB = 0, annual ESAL = 250,000 in design lane, 3 percent traffic growth.

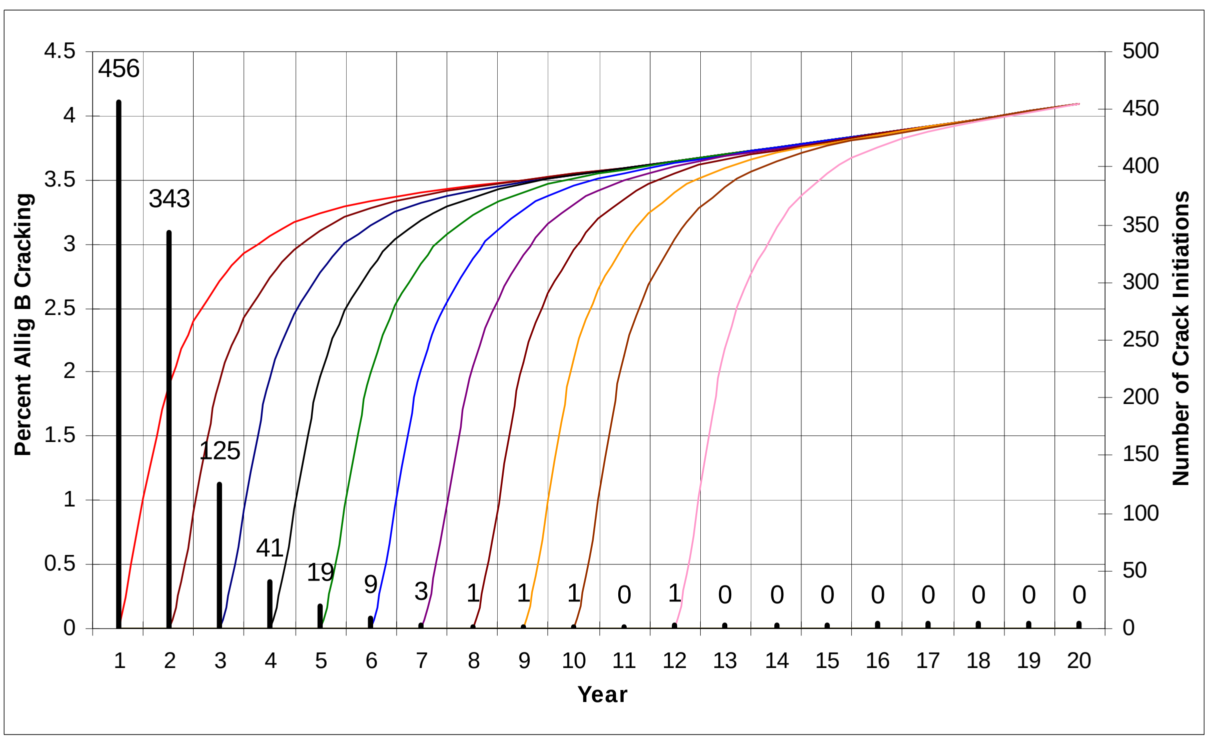

Figure 9: Overlay Type BA, all explanatory variables set at their medians, base dummy variables as in Figure 7, but annual ESAL = 100,000 per year in design lane.

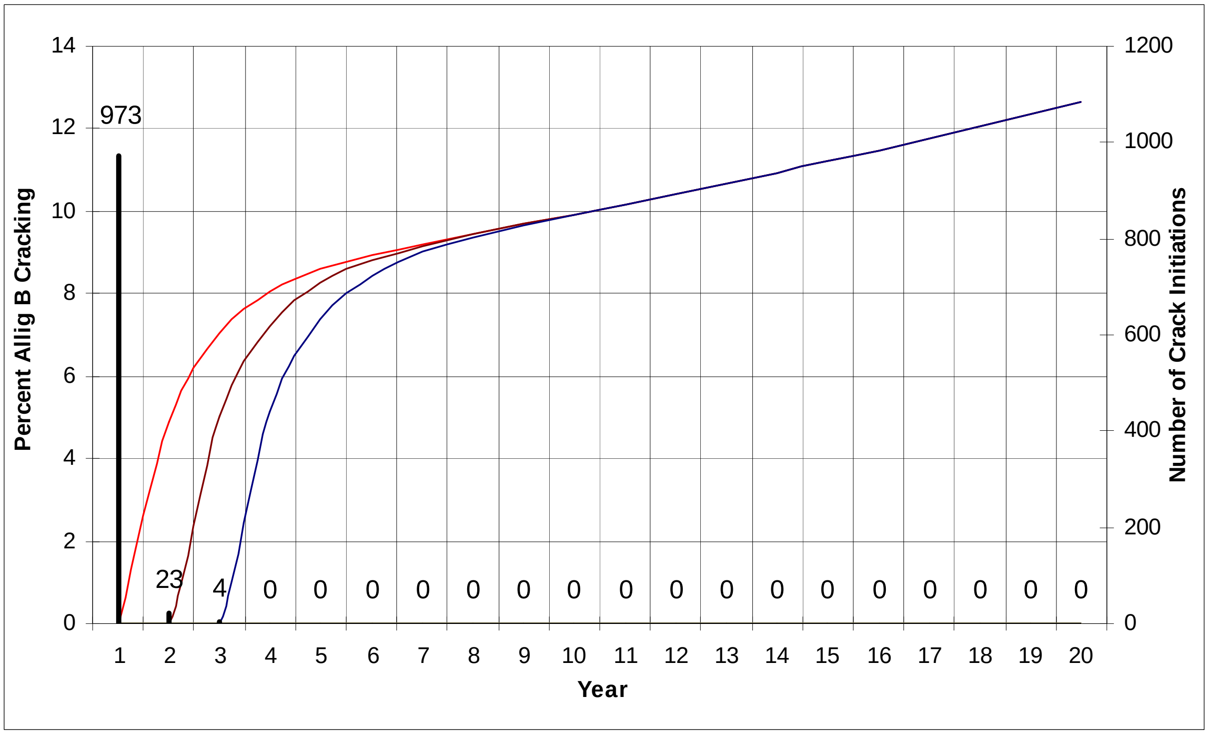

Figure 10: Overlay Type BA, all explanatory variables set at their medians, base dummy variables as in Figure 7, but annual ESAL = 500,000 in design lane per year.

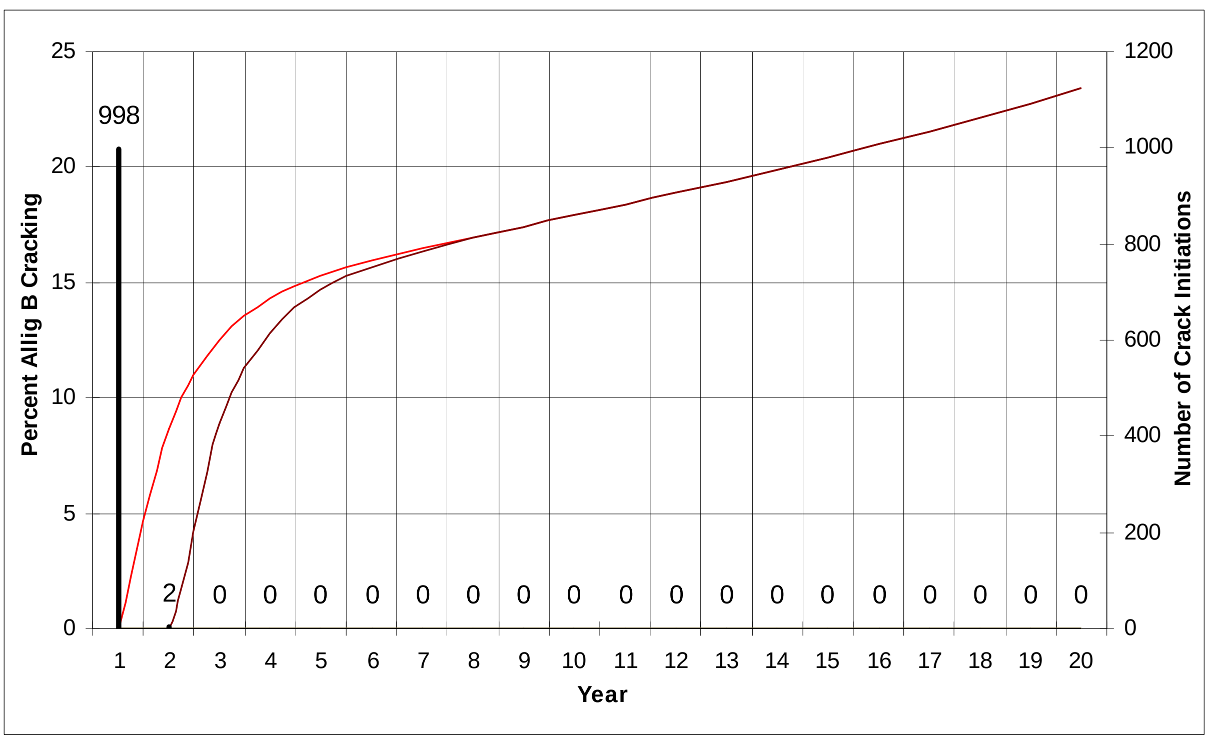

Figure 11: Overlay type BA, all explanatory variables set at their medians, Base dummy variables as in Figure 7, but annual ESAL = 1,000,000 per year in design lane.

The following observations can be made, on the basis of Figure 3 through Figure 10:

- Overlays made of Type AA material consistently perform better than those made with type BA material. The graphs show that, in the median case, overlays of Type AA may crack as late as in the ninth year, whereas the crack initiation of overlays of Type BA occurs in the first two years in the median case. Moreover, for the median case, the maximum cracking percentage around Year 14 (which is the average time interval between overlays in Washington State) is around 4 percent for Type AA and closer to 6 percent for Type BA materials. This behavior was expected given that the coefficients of the dummy variable for Type AA were higher than those for Type BA in both the initiation and progression models.
- The effect of traffic loading is clearly important. As can be seen, both cracking initiation and progression accelerate significantly as loading is approximately doubled from 100,000 ESALs per year to 250,000, then to 500,000 and 1,000,000.

Table 5: AA Median Parameter Values

	Alligator Cracking	Longitudinal Cracking	Untreated Thickness	Surface Thickness	Previous Thickness
Median	0%	30%	6 in.	1.8 in.	6.96 in.

3.6.5 Model Predictions for California Conditions

To illustrate the use of our model system, we applied it to three locations in California. Crack initiation and progression predictions were made for Los Angeles, Sacramento, and Arcata using median values for the pavement properties seen in the Washington State Pavement Management System database.

Traffic volumes were varied to simulate a wide variety of possible traffic situations. As such, tests were run for each city at 125,000 ESALs, 250,000 ESALs, 500,000 ESALs, and 1,000,000 ESALs. Weather data for each of the cities were obtained using the *Climatic Database for Integrated Model* (CDIM) software. All climate data were from the most recent year available, 1997.

3.7 Results

As can be seen by comparing Figure 6 and Figure 7 with Figure 14 and Figure 15 and Figure 22 to Figure 23, there is quite a difference between the performance predictions from the model between California and Washington. For instance, according to scenario run for Washington State shown in Figure 6 (variables at median, traffic: 500,000 ESALs in design lane) fiftieth-percentile crack initiation occurs in Year 3. However, Figure 18, which is run for Arcata’s climate and traffic level, predicts fiftieth-percentile crack initiation in Year 5. In general, according to the model, in Washington it is not uncommon to see the majority of crack initiations begin relatively sooner for California climate, all other variables being equal.

Since the same pavement characteristics are used for both Washington and California predictions, only the climate data is significantly different. Upon looking closer at the data, it also becomes apparent that there is not a great difference between the temperature extremes for the two states. This would imply that the precipitation and freeze-thaw cycles are the determining factor in the large difference seen in crack initiation.

The crack initiation model uses $(Annual\_\Pr ecip)*(FT\_Cycles)$ as one of the explanatory variables. The primary difference between Washington and California climate data is the relative lack of freeze-thaw cycles in California, with none seen in either Los Angeles or Arcata and only one in Sacramento. In Washington State, on the other hand, the median was 20 freeze-thaw cycles.

Crack progression, unlike initiation, shows no overwhelming indication of a strong reliance on climate data. In nearly all cases, the crack progressions were very similar, apparently most affected by loading rather than other factors.

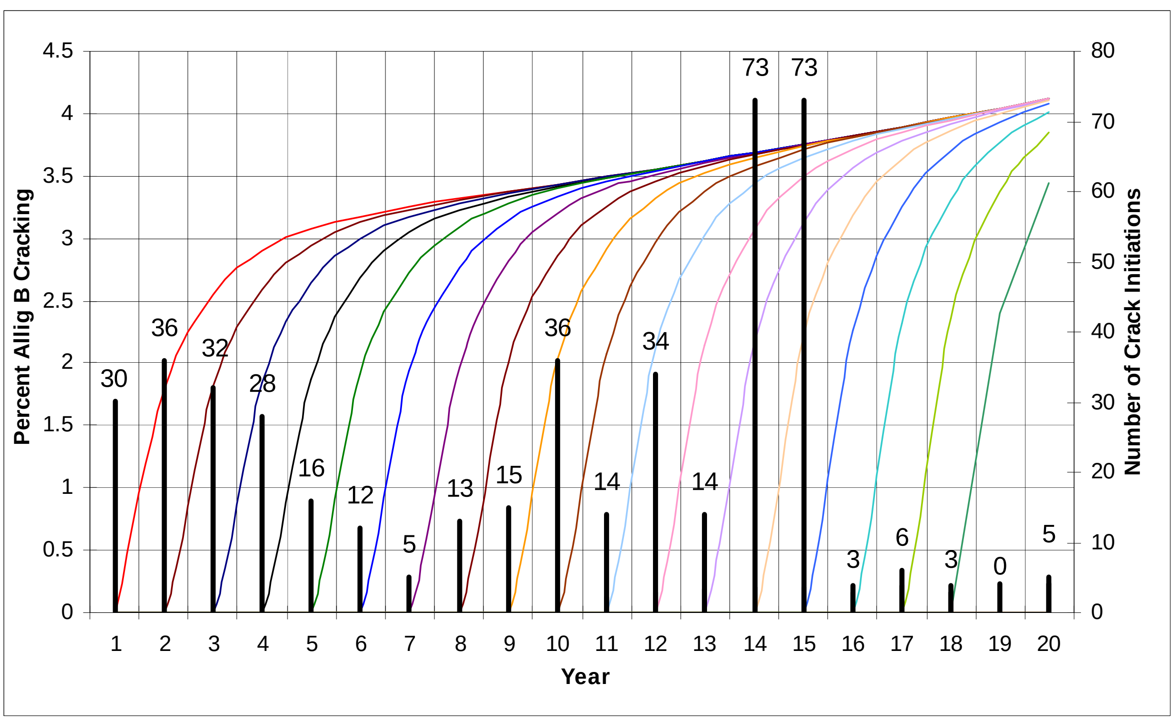

Figure 12: Sacramento—all medians—125,000 ESALs per year in design lane.

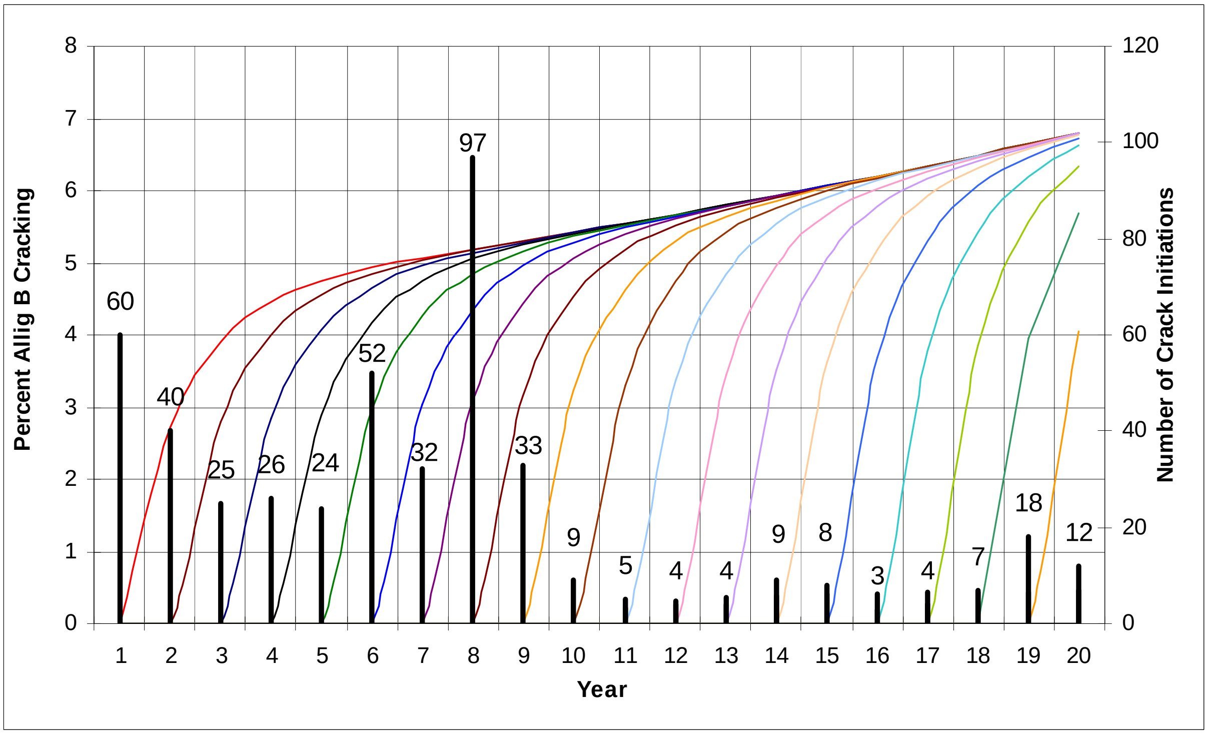

Figure 13: Sacramento—all medians—250,000 ESALs per year in design lane.

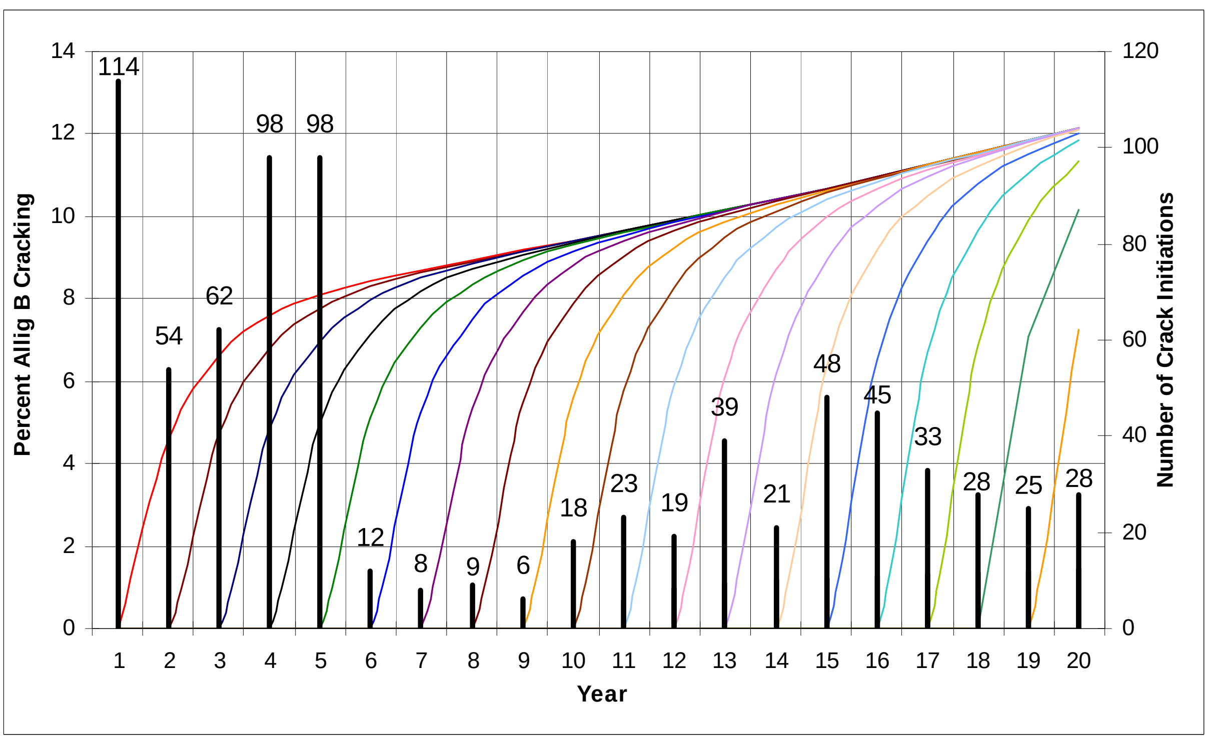

Figure 14: Sacramento—all medians—500,000 ESALs per year over in design lane.

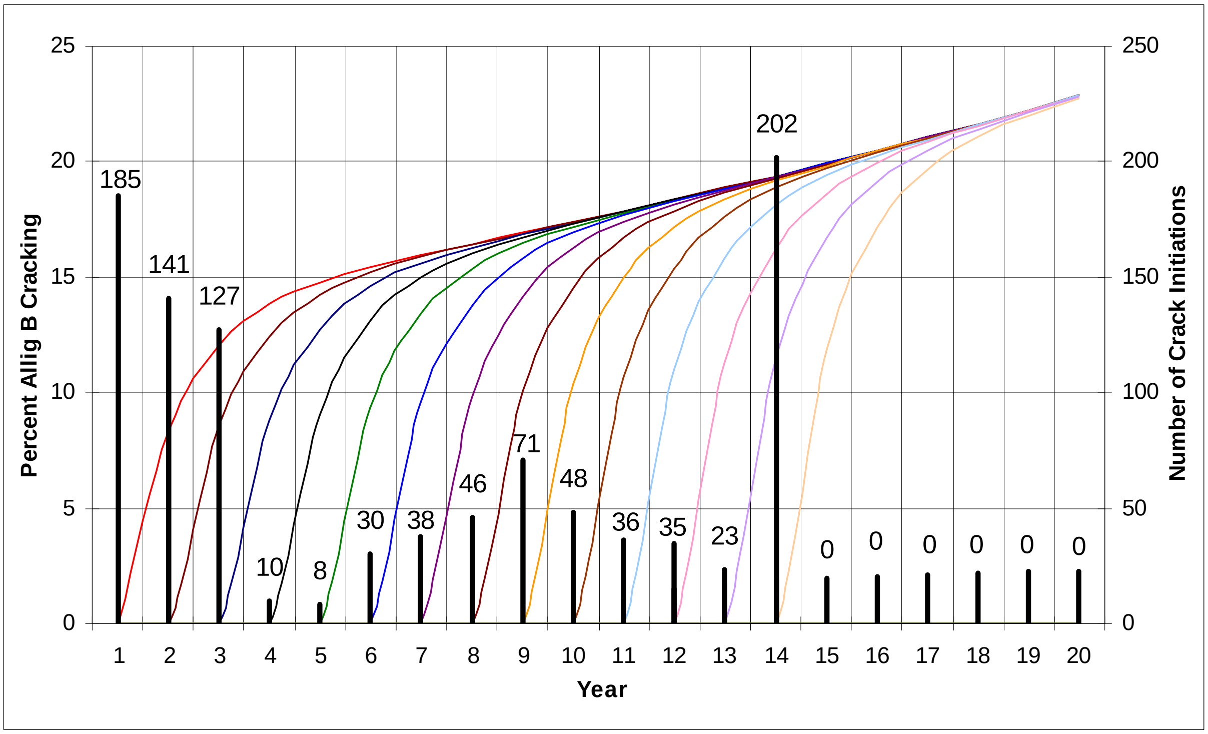

Figure 15: Sacramento—all medians—1,000,000 ESALs per year in design lane.

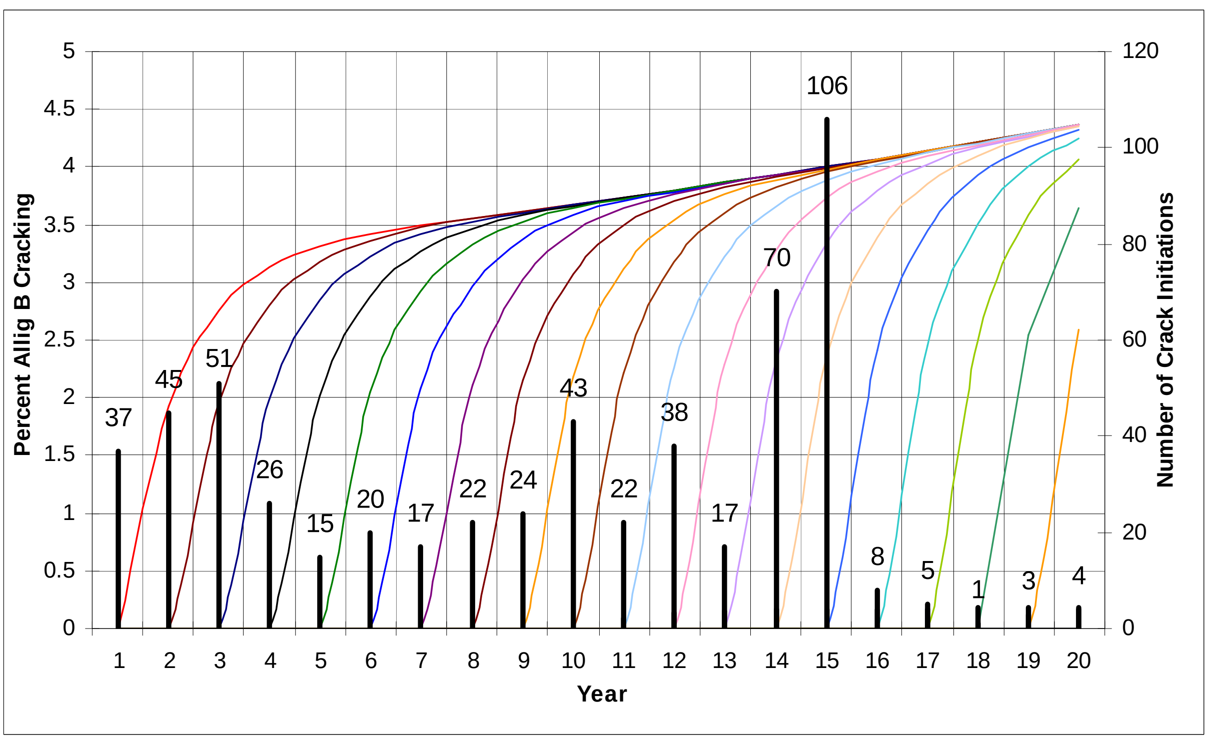

Figure 16: Arcata—all medians—125,000 ESALs per year in design lane.

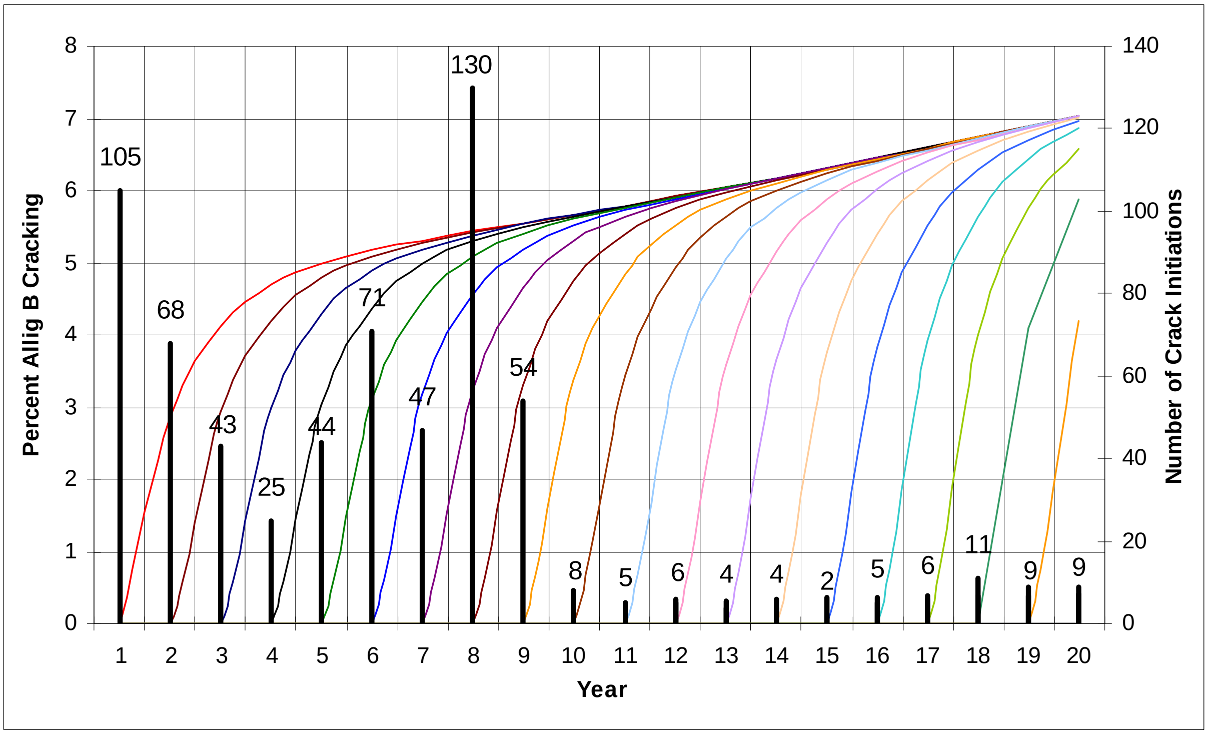

Figure 17: Arcata—all medians—250,000 ESALs per year in design lane.

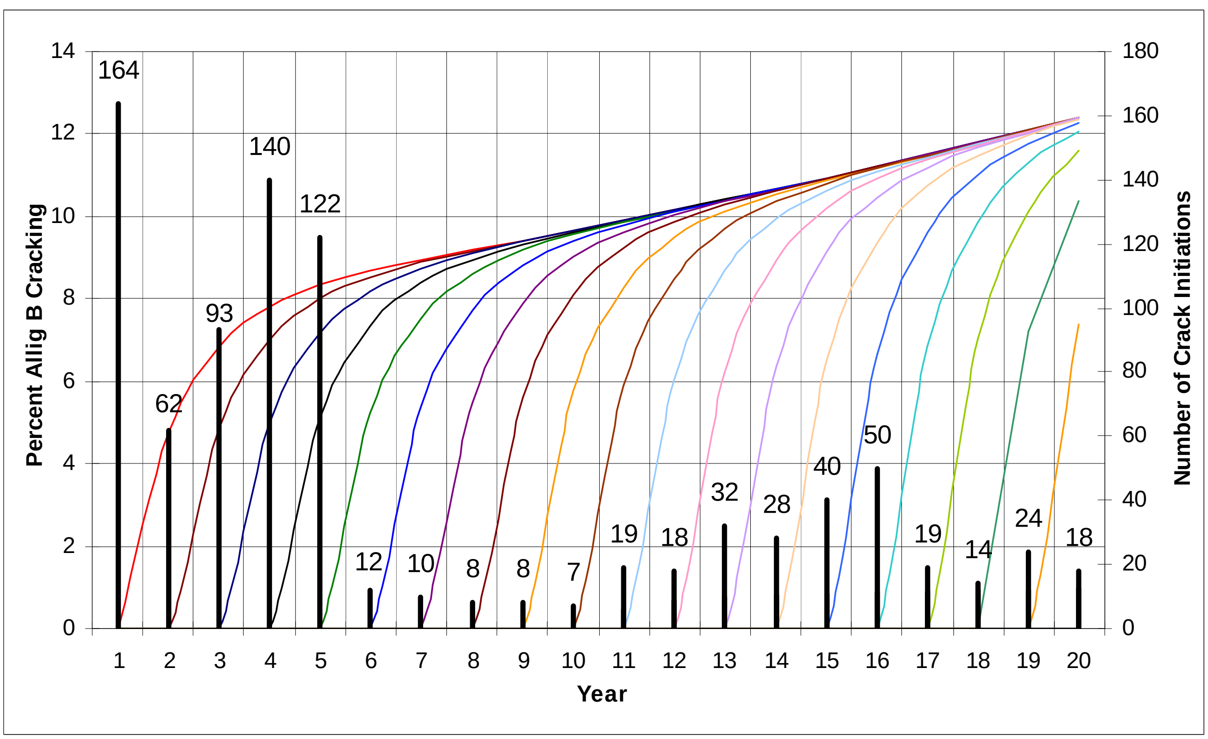

Figure 18: Arcata—all medians—500,000 ESALs per year in design lane.

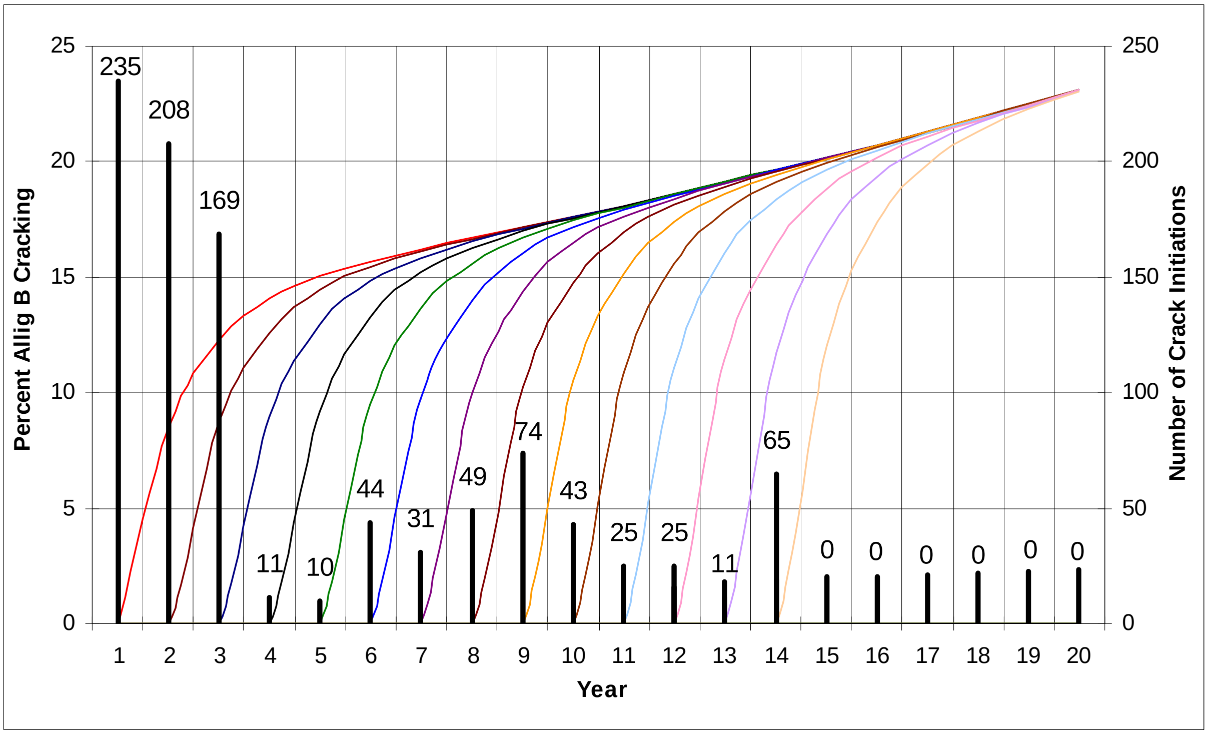

Figure 19: Arcata—all medians—1,000,000 ESALs per year in design lane.

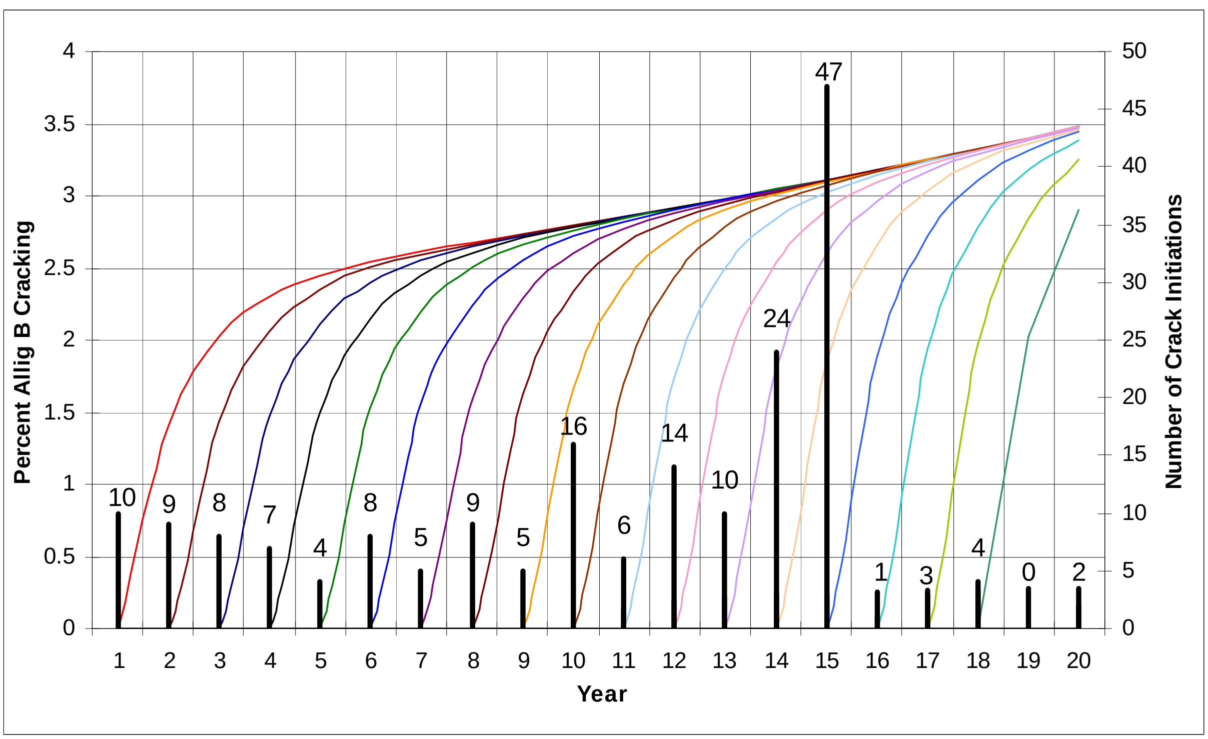

Figure 20: Los Angeles—all medians—125,000 ESALs per year in design lane.

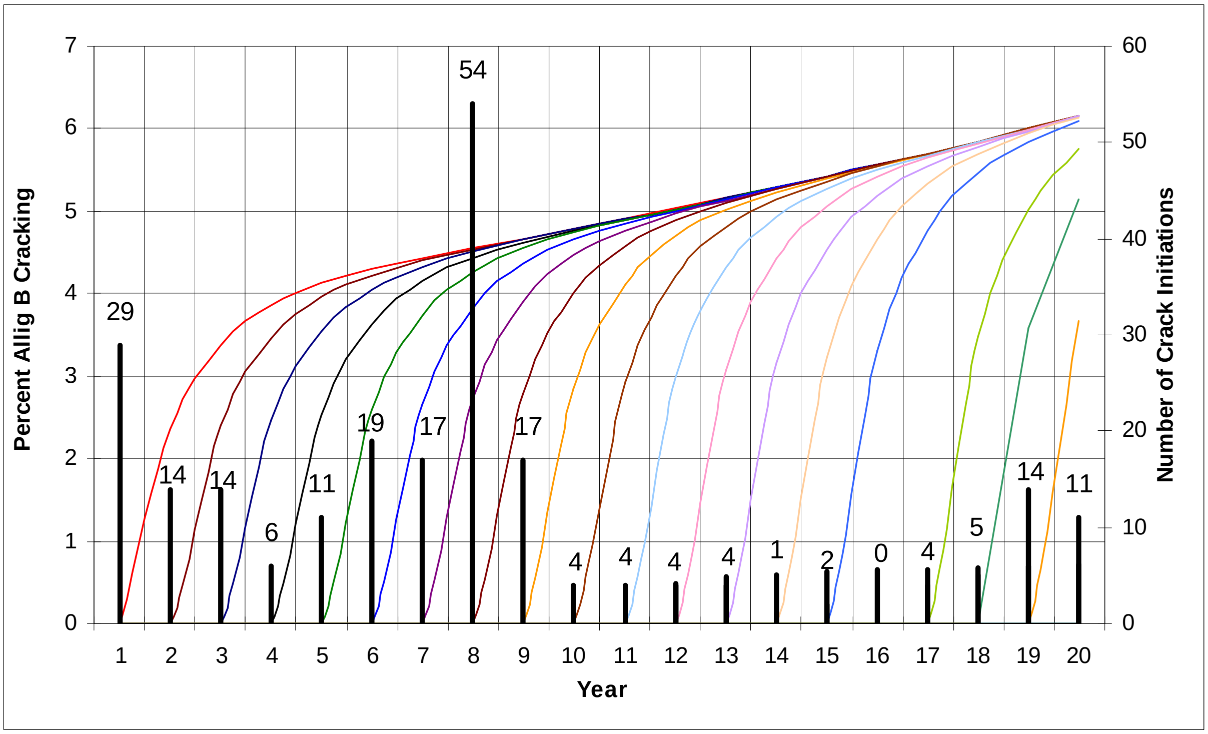

Figure 21: Los Angeles—all medians—250,000 ESALs per year in design lane.

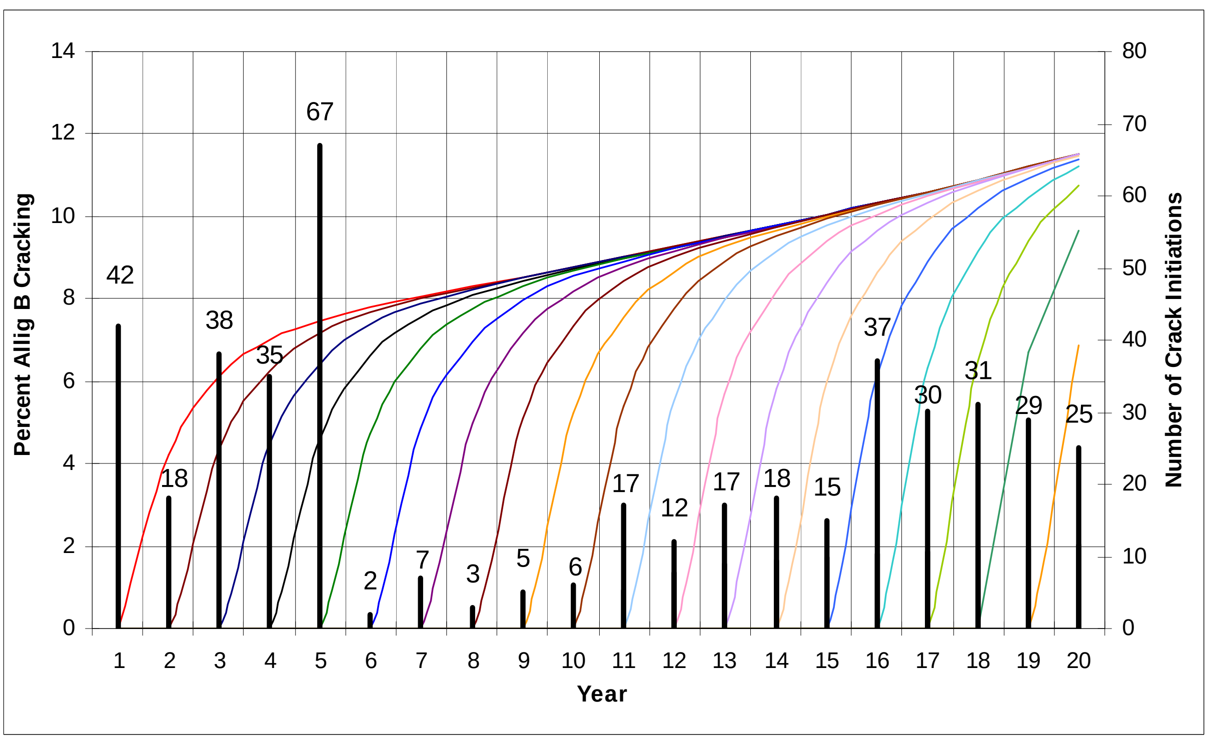

Figure 22: Los Angeles—all medians—500,000 ESALs per year in design lane.

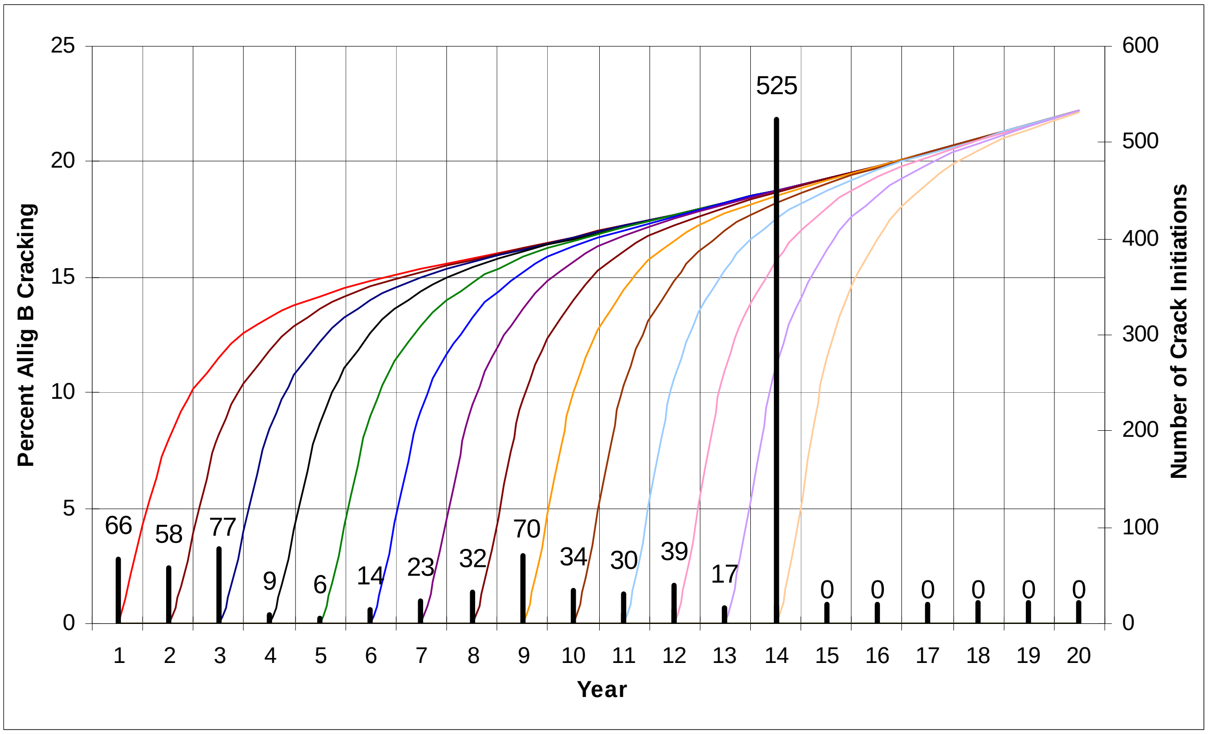

Figure 23: Los Angeles—all medians—1,000,000 ESALs per year in design lane.

4 CONCLUSIONS

4.1 Summary of Research Objectives and Results

In this work, Empirical-Mechanistic (E-M) models for progression of overlay cracking in asphalt concrete pavements were developed using data from Washington State's Pavement Management System (PMS) databases. Performance models are an important component of a PMS and were introduced in detail along with the other PMS components.

An overlay crack progression model was developed in this research. Panel data problems, such as incidental truncation, left censoring, and cross-sectional heterogeneity, were properly addressed and suitable statistical tools were applied. The research shows that a specification that captures the main factors responsible for the overlay crack initiation and crack progression processes, combined with careful analysis of the data, can produce models of sufficient realism for pavement management purposes.

The following explanatory variables were found to be the most relevant predictors of the annual increment in alligator cracking for hot-mix asphalt (HMA) overlays on HMA pavements:

- The alligator cracking in the previous year
- The existing alligator cracking prior to the application of the (last) overlay
- The thicknesses of AC-treated, portland cement-treated and untreated bases
- The thickness of the underlying HMA layers prior to application of the overlay
- The thicknesses of overlays of different material types
- The annual traffic loading in ESALs
- The annual precipitation and annual freeze-thaw cycles
- The average daily minimum temperature during the coldest month and the average daily high temperature during the hottest month.

4.2 Recommendations for Implementation

While the functional form and specification of the cracking initiation model and cracking progression model developed in this report are transferable to Caltrans, the values of the coefficients that were estimated with Washington State DOT data are not directly transferable. This is due to a number of reasons, including differences in materials, environment (at least in the drier and warmer regions of California), and most importantly, maintenance practices.

Washington State DOT's maintenance strategy is to perform pavement preservation mainly with overlays averaging about 0.15 ft (45 mm) thickness, and place few thicker rehabilitation overlays.

Therefore, the following recommendations for implementation are made:

- The developed HMA pavement performance model suite [the cracking initiation model described in report UCPRC-RR-2005-5 (5) and the cracking progression model described in this report] should be tested with California PMS data. These data can either be collected as part of a pilot project or mined from data in the Caltrans PMS database after that database has been populated with information collected over consistently segmented sections. Because of the differences in maintenance policy between Washington State DOT and Caltrans, it is expected that the model parameters will need to be recalibrated.
- Once Caltrans has populated its PMS database with sufficiently extensive condition survey data, these developed HMA pavement models can be updated recalibrated with the California data. Recalibration does not necessarily mean that all parameters will need to be re-estimated. Instead, statistical fusion procedures, such as Bayesian updating, can be used to recalibrate a subset of the coefficients in the model. The coefficients that will need recalibration include the *coefficient for overlay thickness,* because Washington State DOT uses thinner overlays than Caltrans and *the coefficient for existing cracking before overlay.*
- The concave shape of the crack progression trend, observed in Figure 3 through Figure 10 of this report, is the result of unrecorded maintenance activities such as crack sealing or patching. If Caltrans does not use similar routine maintenance, the *coefficient for percent wheelpath with alligator cracking* should also be recalibrated, because the value of that coefficient determines the curvature of the crack progression trend.

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APPENDIX A – SPREADSHEET EXPLANATION

A.1. Introduction

This spreadsheet applies the cracking initiation and progression models described in Partnered Pavement Research Center (PPRC) report number UCPRC-RR-2005-5 (5) and this report, respectively. The spreadsheet predicts the probability distribution of alligator cracking (in each year) for asphalt concrete pavements with asphalt concrete overlays.

Cautious use of the spreadsheet is advised for geographic locations other than Washington State, such as California, because the input data (described below) should be within the ranges of the Washington State data that were used for developing the two models.

A sample simulation using commonly seen inputs is included to serve as an example for how to use the spreadsheet. This example will provide step-by-step instruction for the process of creating a crack initiation and progression prediction.

A.2. Input Data

The user needs to enter data on pavement condition, pavement structure, pavement maintenance, road geometry, climate, and traffic. These input data are summarized in Table 8.

To account for the distribution of truck traffic when two or more lanes are available in one direction, truck factors recommended by AASHTO are used. Table 6 summarizes these values as well as the correction factors used to correct the original model. The correction has already been applied in the spreadsheet and user does not need to input these values in the model.

Table 6: Lane Distribution Chart

No. of Lanes Each Way	% Truck Factor	Default Values	Correction Factor
1	100	100	1.0
2	80-100	90	0.9/0.5 = 1.8
3	60-80	70	0.7/0.333 = 2.1
4	50-75	65	0.65/0.25 = 2.6

Table 7: Input Ranges for Spreadsheet Data

Category	Required Input	Mnemonic Used in Spreadsheet	Units	Recommended Range
Condition	Existing alligator cracking before last overlay (WSDOT definition)	Prev. Allig. Cr.	%	0–60
Condition	Existing longitudinal cracking before last overlay (WSDOT definition)	Prev. Long. Cr.	%	0–100
Structure	AC-treated base thickness	ACTB thickness	Inch	0–6
Structure	PCC-treated base thickness	PCTB thickness	Inch	0–6
Structure	Untreated base thickness	UNTB thickness	Inch	0–28
Structure	Underlying asphalt concrete thickness	Underlying HMA thickness	Inch	0.5–15
Maintenance	Material type of new overlay (WSDOT classification)	Overlay type	-	AA or BA
Maintenance	Thickness of new overlay	Overlay thickness	Inch	0.7–5.4
Geometry	Number of lanes	# Lanes	Each	Integer value
Climate	Annual precipitation	Precipitation	Inch	4–106
Climate	Average monthly minimum temperature of the coldest month (December)	MinTemp	°F	12–39
Climate	Average monthly maximum temperature of the hottest month (July)	MaxTemp	°F	64–93
Climate	Annual number of freeze-thaw cycles	Freeze-Thaw cycle	cycle/year	2–225
Traffic	Traffic loading in all lanes in one direction for first year	Year 1 traffic (all lanes in one direction)	ESAL/year	18,000+
Traffic	Annual traffic growth factor	Annual traffic growth	%	0+

The inputs used for the sample simulation are taken primarily from the default values specified in Table 4. To better simulate realistic conditions, the yearly traffic loading, overlay thickness, and untreated thickness were set at their respective mean values instead of default values. Figure 24 shows these values entered into the data input screen of the spreadsheet.

Condition data:

Prev. Alligator B	Prev. Alligator A
[%]	[%]
0	30

Structure data:

ACB thickness	CTB thickness	Agg base thickness	Underlying AC thickness
[inch]	[inch]	[inch]	[inch]
7	0	6	1.8

Maintenance data:

Overlay type	Overlay thickness
(WSDOT classif.)	[inch]
AA	1.8

Geometry data:

Lanes
[lane]
1

Climate data:

Precipitation	MinTemp	MaxTemp	Freeze-Thaw cycle
[inch]	[°F]	[°F]	[cycle/yr]
13	37	97	0

Traffic data (in all lanes in one direction):

Year 1 traffic	Annual traffic growth
[ESAL/yr]	[%]
1,000,000	3%

Figure 24: Spreadsheet data input screen with sample simulation values.

A.3. Cracking Simulation

Let *t* be a (positive) random variable representing the cumulative traffic loading (in units of ESAL) at which cracking initiates. Based on the input data, the cracking initiation model provides $F_t(t)$, the cumulative distribution function for *t*. For example, $F_t(100{,}000)$ is the probability that a pavement section has started cracking by the time the cumulative traffic loading has reached 100,000 ESALs.

The *inverse transformation method* can be used to simulate *t*. Let U be a random variable with a continuous uniform distribution between 0 and 1. Let *t'* be a random variable defined as follows:

$$t' = \min \{ z, \text{ such that } F_t(z) \geq U \}$$

In other words, t' is the minimum value of z, for which F(z) is at least U. Since F_t given by the crack initiation model is *strictly increasing*, t' can be expressed as follows:

$$t' = F_t^{-1}(U)$$

where $F_t^{-1}(U)$ is the value z that satisfies $F_t(z)=U$.

It is easy to show that t' has the cumulative distribution function F_t (see, for example, *Introduction to Probability Models* by S. Ross). Therefore for a given, randomly generated value of U, the corresponding value of t' represents one simulated value of t.

In order to simulate one value of cumulative loading to failure, one needs to generate one uniformly distributed number and find the corresponding t'. This t' is then used as the cumulative loading to failure for this experiment. Then, for a given year h, say 5, cracking initiates if $h \geq t'$. Using the fact that F_t is strictly increasing, $h \geq t'$ if and only if $F_t(h) \geq F_t(t') = U$. Therefore, if we want to find out whether cracking has initiated at year h, it suffices to check whether $F_t(h)$ is at least U.

The spreadsheet only looks at integer numbers of years. For a given simulated experiment, the spreadsheet applies the cracking progression model starting at integer year y', where y' is the smallest integer year greater than or equal to t'. The percentage of alligator cracking values for all the years up to y' are zero. In each experiment, the spreadsheet finds the percentage of cracking for years 1 through 10, which can then be plotted as the *cracking path*, given that cracking initiates at year y'.

The spreadsheet repeats this experiment 1,000 times. This is called *Monte Carlo simulation*. Since the spreadsheet uses the progression model in a deterministic way, all experiments that have the same year of cracking initiation (e.g., all the experiments that start cracking in Year 2) will have the exact same cracking path, for a given overlay.

A.4. Graph

The spreadsheet creates a graph that shows the cracking paths resulting from the 1,000 simulated experiments. In order to show that different cracking paths have different probabilities, the graph also includes information on the frequency of each cracking path. Figure 25 shows an example of such graph. The x-axis is the year, the left y-axis is the percentage of alligator cracking, and the right y-axis is the number of crack initiations out of 1,000 iterations in a given year.

In this example, each of the 1,000 simulated experiments starts cracking in year 1 or 2. The two curves represent the cracking paths. Each curve has a corresponding vertical bar, which indicates the number of simulated experiments that are characterized by this cracking path. In this simulation, there are 993 experiments that start cracking in Year 1, and their cracking path is represented by the upper curve. Similarly, there are seven experiments that start cracking in Year 2, and their cracking path is the lower curve. This lower curve is horizontal at 0 percent cracking up to Year 2, when alligator cracking initiates and starts increasing.

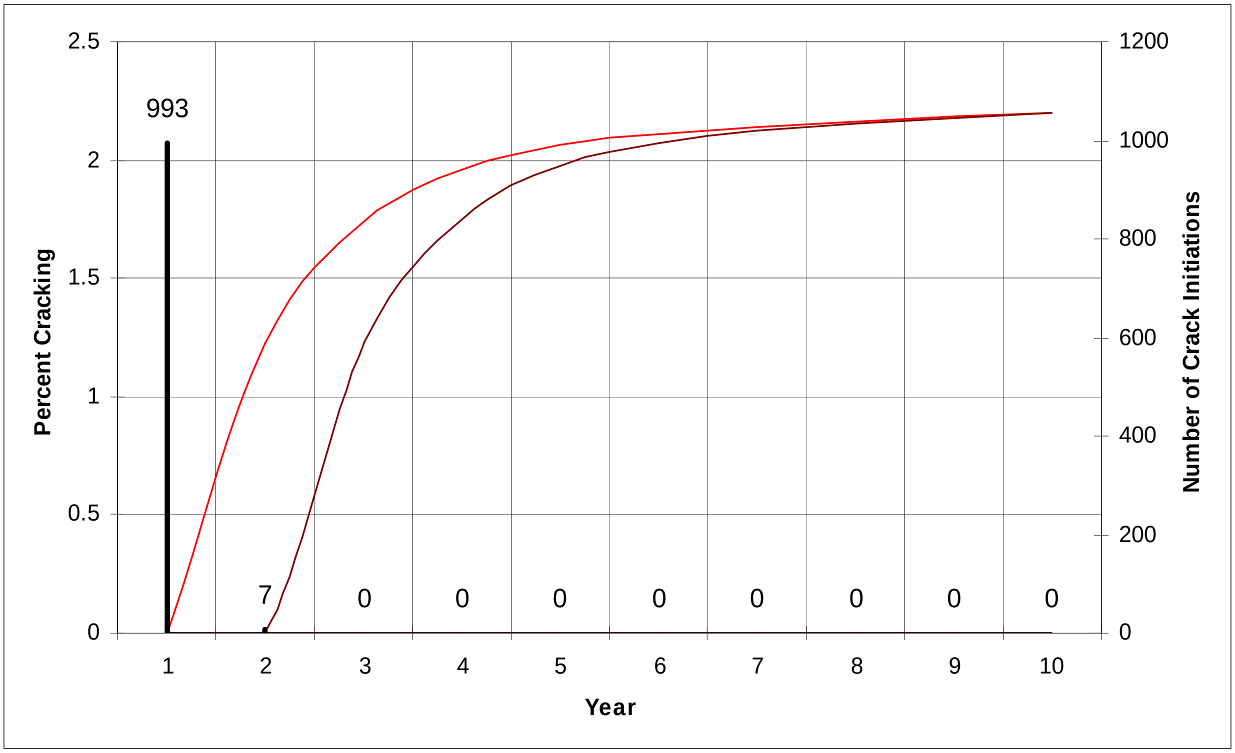

Figure 25: Graphical representation of sample crack initiation and progression.

APPENDIX B: LITERATURE SURVEY OF PERFORMANCE MODELS

Prediction of future performance is needed in pavement management systems at the network and project levels. At the network level, performance prediction is used in preparing long-range budget estimates of the cost to maintain the highway system at a specified minimum performance level or to determine the consequences of future funding levels. At the project level, prediction of future performance is used in life-cycle cost analysis of pavement sections. Performance prediction is also useful in determining the consequences of deferral of rehabilitation actions (45).

B.1. Performance Models for Overall Performance Measures

The early trend in pavement performance modeling was to develop models that predict the overall performance of pavement sections. These models predict the change of a general condition measure for a pavement section in time, given a vector of explanatory variables. Overall performance measures have been designated by several names in literature including: pavement serviceability index (PSI), pavement condition rating (PCR), and pavement condition index (PCI); each is a composite measure of roughness and different distresses, such as rutting and cracking. The current Washington State Department of Transportation Pavement Management System (WSDOT PMS) makes use of performance prediction models for PCI.

Roughness (also referred to as "smoothness" and "ride quality") is an important pavement characteristic because it affects ride quality and vehicle delay costs, fuel consumption, and maintenance costs. Surface distress is defined by the Highway Research Board (46) as, "Any indication of poor or unfavorable pavement performance or signs of impending failure; any unsatisfactory performance of a pavement short of failure." Rutting and cracking are the pavement distresses with most occurrence and implication on pavement management policies.

An example of early overall condition models is the model presented by Scullion et al. (47), and given by:

$$P = P_0 - \alpha t^{\beta} \quad \mathbf{(1)}$$

where P_0 is the initial serviceability index,
t is the total time elapsed to reach a present serviceability index equal to P,
α and β are parameters to be estimated.

Note that the previous model is constructed similarly to the power curve suggested by LeClerc and Nelson (48) and used in the WSDOT PMS.

Another model is the S-shaped, or sigmoidal, model which is given by Riggins et al. (49):

$$P = P_0 - (P_0 - P_f)\exp[(-\rho / t)^{\beta}] \qquad \textbf{(2)}$$

where P_f, α and β are parameters to be estimated.

Another type of model is the B-Spline Model. This model relates an overall measure of pavement conditions to age (50). The B-spline function (51) is a polynomial between each pair of selected points, called knots, along the age axis of the performance curve. Adjacent polynomials join continuously with continuous first and second derivatives. In general, a B-spline with degree k is a continuous function with its first (k-1) derivatives being continuous. Shahin et al. (51) found that B-splines of degree as low as 3 are sufficiently smooth to be useful for approximating the PCI-age data. The serious disadvantage of the B-spline function is that it may exhibit occasional positive slopes suggesting that the PCI increases with age. In addition, the selection of the knots requires advanced engineering judgment.

Other types of models are the recursion models (52, 53), which are essentially time series models of performance index. Other explanatory models such as age, traffic, and structural conditions were sometimes added to these models.

Overall performance models are still currently used by some pavement management agencies. Performance models in the North Carolina State PMS (54) use a power curve to predict the Pavement Condition Rating (PCR) measure versus the pavement age as follows:

$$PCR = C_0 + C_1 Age^{C_2} \qquad \textbf{(3)}$$

where C_0, C_1, and C_2 are constants to be estimated.

Gulen et al. (55) developed a PCR model for Indiana roads given by:

$$PCR = A_0 + A_1 Age + A_2 PV \qquad \textbf{(4)}$$

where *Age* is the age of the overlay, and *PV* a dummy variable that is equal to 1 for concrete pavements and 0 for bituminous pavements. A_0, A_1, and A_2 are parameters to be estimated.

B.2. Performance Models for Individual Distresses

Although performance models using composite indices of pavement condition (PCR, PSI, PCI, etc.) such as those summarized above are currently used widely in practice, in reality, overall pavement performance depends on the level of several different distresses such as rutting and cracking, as well as on roughness. These distresses occur due to different physical mechanisms and have different implications on Maintenance, Repair and Reconstruction (MR&R) strategies. Therefore it is more appropriate to model these distresses separately. In order to do so, pavement engineers and researchers used different approaches to develop distress specific performance models. These approaches generate models that can be generally divided into the following categories:

- Mechanistic and Mechanistic-Empirical models
- Empirical and Empirical-Mechanistic models

B.3. Mechanistic and Mechanistic-Empirical Models

In general, Mechanistic models are based on the use of material behavior and pavement response functions, which are believed to represent the actual behavior of the pavement structure under the combined actions of traffic and the environment. Although there are currently various attempts in this direction, a comprehensive and reliable mechanistic pavement model has yet to be developed. Mechanistic models require too much data to be used for pavement management systems.

Mechanistic-Empirical models make use of material characterization (laboratory or in situ testing) and pavement response models (usually multilayer linear elastic or finite element type models) to determine pavement response critical to each distress mode (i.e., cracking, rutting, etc). This response is, in turn, correlated to pavement performance and finally calibrated to an actual pavement structure. Both pavement test sections and in-service pavement sections are used for this purpose. The models are usually calibrated by applying a bias correction factor (usually referred to as the shift factor or transfer function) (56, 57). Mechanistic-Empirical models are becoming used more frequently for project-level design. They are, however, too expensive to use for pavement management systems because of the amount of data that they require.

Empirical performance models have proven to be the most appropriate models for pavement management and will be discussed in more detail in the next section.

B.4. Empirical and Empirical-Mechanistic Models

In Empirical and Empirical-Mechanistic models, the dependent variable is some indicator of pavement performance. Both subjective indicators, such as overall performance measures (riding quality, serviceability, condition index, etc.), and objective indicators, such as distress specific measures (roughness, rutting, cracking, etc.), are used as dependent variables.

These performance indicators are related to one or more explanatory variables, such as pavement structural strength, traffic loading, and environmental conditions. These models are often developed based purely on statistical considerations without any attempt to represent the actual physical phenomenon underlying the performance process. Different researchers have approached the development of these models in different ways, especially in the way in which the form of the model specification is developed.

In the majority of empirical models found in the literature, explanatory variables are used and discarded solely on the basis of consideration of the statistics of their parameters. Often, relevant variables are discarded, owing to low statistical significance (as measured by *t* statistics). On the other hand, irrelevant variables are often incorporated into the models, based on the same considerations. Any models developed following such an approach will undoubtedly suffer from specification biases. Most of the specifications are a linear combination of the available regressors, and the criterion for the selection of the best specification among several alternatives is to obtain the best possible fit to the data.

A few researchers have used specification forms that simulate the actual physical process of deterioration. In their work, the form of the specification, even though relatively simple (by comparison with the actual physical phenomenon and Mechanistic-Empirical models) is not constrained to linear equations. This approach is often referred to as the Empirical–Mechanistic approach and is further discussed in this section (58).

Two broad categories of Empirical-Mechanistic models have been used in modeling the pavement condition deterioration process: Deterministic models and Probabilistic models.

The Deterministic model assumes that pavement behavior follows a predetermined pattern that can be formulated by a specific mathematical expression relating the considered pavement performance indicator to one or more explanatory variables. However, inherent variability of material properties, environmental conditions, and traffic characteristics cause pavement performance to inherit random characteristics. Therefore by disregarding the uncertainty observed in pavement deterioration modeling, the Deterministic models tend to oversimplify the process of pavement deterioration. On the other hand, Probabilistic models treat pavement condition measures such as crack, roughness, and rut development as random variables, and therefore are able to incorporate the uncertainty associated with pavement deterioration. Examples of both Deterministic and Probabilistic models are presented below.

B.5. Deterministic Models

The AASHO cracking model (46) is one of the early most used deterministic empirical models. Although its functional form was relatively arbitrary, the model has been widely accepted and forms the basis for most current pavement design procedures in the world today. It relates the traffic repetition (dependent variable) to pavement thickness and load type (explanatory variables):

$$W_c = \frac{A_0(a_1D_1 + a_2D_2 + a_3D_3 + a_4)^{A_1} L_2^{A_3}}{(L_1 + L_2)^{A_2}} \quad \textbf{(5)}$$

where Wc = Number of weighted axle applications sustained by the pavement before appearance of Class 2 Cracking;
D_1, D_2, D_3 = Thickness of surfacing, base and sub-base respectively, in inches;
L_1 = Nominal axle load, in kips;
L_2 = 1 for single axle configuration and 2 for tandem axle configuration;
a_1, a_2, a_3, a_4 = Coefficients that were assigned earlier;
A_1, A_2, A_3, A_4 = Regression coefficients.

Although the AASHO model was widely accepted and used, it nevertheless had several defects. One of the defects is that the analysis did not account for censoring. Censoring occurs when cracking is not actually observed. Left censoring occurs when the section has cracked before the first inspection, and right censoring occurs when the section has not cracked at the last inspection or by the time the experiment ended. Right-censored data was frequent in the AASHO Road Test and were not properly accounted for in the model, which led to a biased model. (Censoring is further discussed in Chapter 3.)

Another problem of the AASHO model is that it is arbitrary. L_1 and L_2 for example have different units and were added together. Moreover the coefficients a_1, a_2, a_3, a_4 were determined *a-priori* instead of being estimated simultaneously with the other parameters. a_1, a_2, a_3, a_4 were used to calculate the Structural Number (SN), a measure of the strength of the pavement. The general equation for SN reflects the relative importance of the layer coefficients (a_i) and thickness (D_i):

$$SN = \sum_{i=1}^{3} a_i D_i \quad \textbf{(6)}$$

The estimated values of the coefficients, a_1, a_2 *and* a_3, were: 0.33, 0.10, and 0.08 respectively.

Performance models were developed either separately for cracking initiation and cracking progression, or both initiation and progression were expressed in one model.

Parsley and Robinson (59) and Hodges et al. (60), as part of the Transportation Research Laboratory (TRL) road costs study in Kenya, combined cracking initiation and progression in one relation expressed in terms of cracking and patching. The cracking progression model predicts the incremental change in the area of cracking as a function of the modified structural number and the incremental cumulative traffic loading since the most recent resurfacing. The incremental form of the cracking progression models is as follows:

$$\Delta(C+P)_i = \alpha SN^{-SN}\Delta NE \qquad \mathbf{(7)}$$

where *(C + P)* = Sum of areas of cracking and patching (m^2/km/lane);
SN = Structural number;
NE = Cumulative traffic loadings since latest resurfacing;
α = Regression coefficient.

The Queiroz-GEIPOT models (61, 62) are examples of models that separate crack initiation and the rate of crack progression. The dependent variable in their crack initiation model is the number of equivalent single axles to initiation, and the explanatory variable is the structural number. The initiation model is given by:

$$Log_{10} N_c = \alpha + \beta \log_{10} SN \qquad \mathbf{(8)}$$

where, N_c = The number of Equivalent Single Axle Loads (ESALs) needed to initiate cracking;
SN = Structural number;
α, β = Regression coefficients.

The progression model predicted the percentage of area cracked as a function of the structural number, traffic, and age of the pavement as follows:

$$CR = \alpha + \beta LN / SN + \gamma ALN \qquad \mathbf{(9)}$$

where, *CR* = percentage area cracked;
LN = logarithm to the base 10 of the number of cumulative equivalent axles;
A = pavement age since construction or overlay (years);
SN = structural number;
α, β, γ = regression parameters.

Oliver (63) presented a crack initiation model for chip seals:

$$Y = \frac{A_0}{(A_1 T + A_2)^2} \tag{10}$$

where, Y = number of years to reach crack initiation;
T = average site air temperature.
A_0, A_1, and A_2 = parameters to be estimated.

Shin (64) presented a crack progression model of the following form:

$$cr_{it} = \beta_0 SN_i^{\beta_1} ESAL_{it}^{\beta_2} \tag{11}$$

where, cr_{it} = area cracked for pavement *i* at time *t*;
SN_i = Structural Number of pavement section *i;*
ESAL = Cumulative traffic expressed in Equivalent Single Axle Load (ESAL);
β_0, β_1, and β_2 are parameters to be estimated.

B.6. Probabilistic Models

Infrastructure deterioration is a stochastic process that varies widely with several factors, many of which are generally not captured by the available data. Therefore, Probabilistic models are used to predict the deterioration of infrastructure facilities such as pavement surfaces. Two types of Probabilistic models have been used for infrastructure facility deterioration prediction: state-based and time-based models.

State-based models predict the probability that a facility will undergo a change in condition-state at a given time, conditional on an array of explanatory variables such as traffic loading, environmental factors, design attributes, and maintenance history. Typical examples of a state-based model are the Markov and semi-Markov processes. In recent years, researchers have refined the simple Markovian transition probabilities that have been used in infrastructure management, by accounting for the effects of age (time heterogeneity) and deterioration history, thus relaxing the Markovian assumption (or equivalently, imposing it on an augmented state which includes the history of the process). At the same time, econometric methods such as Poisson regression, Probit regression, and duration models have been used to estimate the parameters of these models and to compute the transition probabilities (65, 66, 67, 68).

Time-based models, on the other hand, predict the probability distribution of the time taken by an infrastructure facility to change its condition-state, conditional on an array of explanatory variables such as traffic loading, environmental factors, design attributes, and maintenance history. Such models have been used frequently in pavement deterioration modeling to predict the time to cracking initiation (69) or the number of axle load repetitions needed to reduce serviceability below an acceptable level (70).

It is important to observe that while the two modeling approaches are based on different econometric techniques, they have a number of similarities. In particular, it is possible to use one modeling approach to predict the dependent variable of the other. For example, given a set of condition-state transition probabilities, one can derive the probability distribution of the time to condition-state change. Similarly, given a distribution of time-in-state, it is possible to compute time-dependent transition probabilities. The state-based model gives the probability of *N* events (transitions in condition-state) in a fixed time period, while the time-based model gives the probability density of the inter-event times (time between transitions in condition-state). Therefore, the decision of which Probabilistic approach to use must be based on empirical considerations. Specifically, the nature of the condition data available for model development may favor one approach over the other. If continuous (or almost continuous) observations of facility condition over a long time window (i.e., a time window that is longer than the maximum time needed for condition-state transition) are available, then it is possible to develop a time-based model because accurate observations of the dependent variable are possible.

On the other hand, if inspections are made infrequently or if the available data only span a relatively short time window, then the measurement of the time between condition-state transitions will suffer from potentially large measurement errors or from severe censoring, both of which may render the resulting time-based models inaccurate. In such situations, a state-based model would be the better approach (71).

With regard to Probabilistic Time-Based Models, Paterson's empirical work, based on data from the World Bank's Highway Design and Maintenance (HDM-III) project was one of the most comprehensive attempts to develop Probabilistic time-based models for different types of pavement distresses (72). The World Bank's Highway Design and Maintenance (HDM) models (72) use a Probabilistic Parametric Duration model to predict crack initiation, where the dependent variable is the probability distribution of the time to cracking. The HDM-III crack initiation model used a Weibull hazard function, *h(t)* of the following form:

$$h(t) = \gamma \exp(-\gamma\mu) t^{\gamma-1} \quad \textbf{(12)}$$

The parameter μ is replaced by a linear function of explanatory variables **x**, and is given by $\mu = \beta'\mathbf{x}$. β and γ are parameters to be estimated.

The resulting model for prediction of expected cumulative traffic loading to crack initiation is:

$$TE_{CR2} = \beta_1 SN^{\beta_2} e^{\beta_3 SY} \quad \textbf{(13)}$$

where, TE_{CR2} = mean cumulative traffic loading at initiation of narrow cracking (in millions of ESALs);
SN = Structural number;
$SY = SN^4 / (1000\ YE_4)$, where YE_4 is the annual traffic loading (in millions of ESAL/lane/year);
$\beta_1, \beta_2, \beta_3$ = parameters to be estimated.

Models with separate predictions for initiation and progression have the advantage that they can be estimated separately, allowing a better description and understanding of initiation and progression, processes that are physically different.

Van Dam et al. (73) analyze the Strategic Highway Research Program (SHRP) Long-Term Pavement Performance (LTPP) data by using the Probabilistic Failure-time Crack Initiation models previously developed for use in HDM-III. On the basis of that analysis, they conclude that the HDM-III models do not accurately capture the climatic factors that play a role in linear cracking initiation typically observed in North America. When considering only fatigue-related cracking, HDM-III models could be successfully fit to the data, but concerns related to the shape parameter call into question their general applicability. It is concluded that although some aspects of this analysis suggest that HDM-III models adequately model fatigue-related crack initiation in LTPP pavement sections, overall the results are inconclusive and a more in-depth analysis needs to be conducted.

The two models, derived from the HDM-III models, which best fit the LTPP data are given by Van Dam et al. (73):

$$TY_{cr} = a_0 \exp(a_1 YE_4 + a_2 SNC) \quad \textbf{(14)}$$

$$TY_{cr} = a_3 \exp\left[a_4\left(\frac{YE_4}{SNC^2}\right)\right] \quad \textbf{(15)}$$

where $TYcr$ = The expected age in years of the surfacing at age and temperature-related cracking initiation;
SNC = Modified Structural Number;
YE_4 = Traffic loading rate in millions of equivalent single axle loads (ESALs) per lane per year;
a_0, a_1, a_2, a_3, a_4 and a_5 are coefficients to be estimated.

Shin and Madanat (74) and Shin (64) used a Weibull model to estimate a crack initiation model. The parameter μ was defined by Shin (64) as:

$$\mu = \beta_1 + \beta_2 D_1 + \beta_3 D_2 + \beta_5 Type \times Load + \beta_6 (1 - Type) \times Load \qquad \textbf{(16)}$$

where D_1 = Surface thickness in inches;
D_2 = Base thickness in inches;
D_3 = Subbase thickness in inches;
Load = Nominal axle load (in kips);
Type = Single dummy variable, 1 for single axle and 0 for tandem axle;
$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are parameters to be estimated.

Colucci et al (75) estimate the survival function *S* of pavement sections in different regions in Puerto Rico as a function of cumulative traffic to failure w_f. The survival function defined by Colucci et al. (75) is given by:

$$S(w_f) = e^{-\left(\frac{w_f}{\alpha}\right)^{\delta}} \qquad \textbf{(17)}$$

where α and δ are parameters to be estimated.

De Lisle et al. (76) presented a study for network-level pavement performance prediction that incorporates censored condition data. They used data from the New York State Department of Transportation (NYSDOT) to model the survival function of the dependent variable, defined as qualitative measure of the extent of cracking on the pavement surface, for different regions in New York State. De Lisle et al. (76) assumed a Weibull distribution of the survival function and used time as the only explanatory variables in their models. While De Lisle et al. (76) applied a proper modeling approach by using duration models and accounting for right censoring; their model included only time as explanatory variable, and therefore it is simplistic and not very useful to determine pavement management policies.

Loizos and Karlaftis (77) developed surface distress prediction models for pavement crack initiation on the surface of flexible and semirigid pavements (asphalt placed on cement-treated base) on the basis of a large and recent data set collected from in-service pavements in 15 European countries by using the principles of stochastic duration models. They found that, as expected, construction, traffic, and climatic factors affect pavement distress. They also compared several parametric forms of the survival function (Lognormal, Loglogistic, Weibull, and Exponential) using the likelihood ratio test and found that the lognormal functional form, in contrast to the findings of previous studies, best describes the distress initiation process. This last finding however was not very convincing since the likelihood ratio test for the

Lognormal, Loglogistic, and Weibull models were roughly similar and the differences might not have been significant. Moreover, Loizos and Karlaftis (77) combined cracking in pavement overlays as well as cracking in the first pavement layer in their analysis, while in practice they should be separated as some factors that affect overlay cracking (reflection cracking) do not contribute to crack initiation in the first pavement layers.

Wang et al. (78) presented a study that analyzed the development patterns of fatigue cracking shown in flexible pavement test sections of the LTPP program. A large number of LTPP test sections exhibited a sudden burst of fatigue cracking after a few years of service, and in order to characterize this type of LTPP cracking data, Wang et al. (78) conducted a survival analysis to investigate the relationship between fatigue failure time and various explanatory variables. They used an Accelerated Failure Time model. The Accelerated Failure Time model assumes that the effect of independent variables on a failure time distribution is multiplicative on the event time. One possible form of the Accelerated Failure Time model is as follows:

$$T = e^{\beta'\mathbf{x}} T_b \qquad \textbf{(18)}$$

where T is the failure time;
T_b is the failure time associated with a baseline distribution function;
$\mathbf{x}$ vector of the explanatory variables;
β is a vector of parameters to be estimated by maximum likelihood.

Wang et al. (78) assumed different parametric distributions for the baseline function, such as the Loglogistic, Weibull, Lognormal, Exponential, and Generalized gamma distributions. Since the assumed baseline models above are nested within the Generalized Gamma distribution, or in other terms represent a special case of the Generalized Gamma distribution, the likelihood-ratio test can be used to compare these nested models. Wang et al. (78) found that the Generalized Gamma distribution for the baseline function represent the best fit for the LTTP data.

With regard to Probabilistic State-Based models, one of the commonly used probabilistic modeling approaches is the method of Markov chains. Markovian transition models have been employed extensively for modeling infrastructure performance (6, 40, 7). The key to modeling the condition deterioration process using a Markov chain is to establish a matrix of appropriate transition probabilities.

Historically, two methods have been employed for the derivation of the transition probabilities depending on the extent of the available pavement condition survey data. Due to the scarcity of data in the initial stages of a PMS, pavement expert knowledge is usually sought to construct a reasonably accurate transition probability matrix that is stationary or invariant with respect to the condition deterioration process. Considering the subjective nature of pavement expert knowledge and the wide variation of the impact of the associated variables on the pavement deterioration, the adequacy of the stationary and subjective transition probability matrix in representing the deterioration process is questionable.

On the other hand, in an established and well-functioning PMS with a wealth of historical condition survey data, the transition probability matrix is usually deduced from statistics of pavement condition data. In this regard, a case study has been reported by Wang et al. (79), who developed transition probability matrices from statistics of survey data for the Arizona Department of Transportation. Mishalani and Madanat (68) also derived transition probabilities from Stochastic Duration models. However, most highway agencies that adopt the Markov chain–based performance model in their PMS still rely on static transition probabilities.

Researchers have recently applied econometric methodologies in modeling infrastructure deterioration using condition-rating data. Combining well-established methodologies and accurate facility characteristics data, these models can be considered more appropriate than the Markov chains based on stationary transition probabilities. As an example, Madanat et al. (66) introduced an ordered Probit model for estimating transition probabilities from infrastructure inspection data. The above model assumes the existence of an underlying continuous random variable and therefore allows the latent nature of infrastructure performance to be captured. Then an ordered Probit model is used to construct an incremental discrete deterioration model in which the difference in observed condition rating is an indicator of the underlying latent deterioration. Finally this model is used to compute a nonstationary, i.e., time-dependent transition matrix. Based on the previous work, Madanat et al. (67) proposed an improved Probit model with the specification of random effects to account for the heterogeneity and extended the model to investigate the state dependence.

Yang et al. (80) presented a detailed study on the use and development of state-based Markovian models. They established a simple relationship between the transition probabilities of pavement crack condition and all relevant explanatory variables through a logistic model to facilitate the computation of dynamic transition probabilities that truly represent the state dependency of the pavement deterioration process. The issue of state dependency of transition probabilities was addressed by including the lagged pavement crack condition index itself as one predictor in the model specification. Then, a recurrent Markov chain was constructed based on the logistic model and a computationally simple procedure was established for crack condition forecasting.