Development of Empirical and Mechanistic Empirical Performance Models at Project and Network Levels

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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ABSTRACT

Performance prediction models are a vital component in pavement management systems (PMS). Along with decision trees, prediction models are used to set priorities for maintenance and rehabilitation planning, and ultimately for budget allocations at the network level. Reliable and accurate prediction of pavement deterioration over time helps transportation agencies accurately predict future spending and save significant amounts of money. Within a PMS, raw performance data is often converted into aggregated performance indices, such as the Riding Comfort Index (RCI), to quantify the road's roughness, or the Distress Surface Index (SDI), to quantify accumulated pavement distress. Technology has evolved rapidly in the last two decades, making data collection for pavement conditions (i.e. roughness and distress data) more feasible for transportation agencies. However, transportation agencies, especially at the municipal level, only maintain condition data to evaluate the present pavement status. Only limited attempts have so far been made to develop or enhance existing deterioration models in pavement management systems, using periodically collected condition data over time. A well-maintained historical database of pavement condition measurements and performance indices can be a useful source for the development of performance prediction models. In some cases, however, the database may contain incomplete data and insufficient information to develop reliable performance models. In addition to inconsistency in the historical performance data, the age of the pavement or the date of the last maintenance/ rehabilitation treatment may not be available to develop the pavement performance over time.

The goal of this research is to develop enhanced empirical performance models capable of capturing the unpredictable and indeterminate nature of pavement deterioration behavior. This research provides a methodology to develop empirical models in the absence of the construction and/or rehabilitation dates. The models developed in this research use limited available historical data, and examine different parameters, such as pavement thickness, traffic pattern, and subgrade condition.

Parameters such as the date of pavement construction and the age of the pavement are also incorporated into the proposed models, and are constrained by local experience and engineering judgment. A linear programming optimization technique is employed to develop the empirical models presented in this research. The approach demonstrated in this research can also be expanded to account for additional parameters, and can easily be adapted to match the needs of different agencies based on their local experience.

In addition, the current research develops a second set of deterioration models based on mechanistic-empirical principles. Models incorporated into the mechanistic-empirical design guide are locally calibrated. A genetic algorithm optimization technique is employed to guide the calibration process, in order to determine the coefficients that best represent pavement performance over time. The two sets of performance models developed in this research are compared at both the project and network level of analysis. A decision-making framework is implemented to incorporate the two sets of models, and a comprehensive life cycle cost analysis is carried out to compare design alternatives in the project level analysis. The two model sets are also evaluated at the network level analysis using a municipal pavement management system. Two budget scenarios are executed, based on the developed performance models, and a comparison between network performance and budget spending is presented. Finally, a summary and current research contribution to the pavement industry will be presented, along with recommendations for future research.

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1.0 Introduction

1.1 GENERAL

Performance measures are essential indicators for transportation agencies in order to effectively maintain an adequate level of pavement service in the most cost effective manner. Pavement distress conditions and roughness are among the key performance indicators being used widely across Canada and globally to evaluate pavement performance and ultimately determine the most effective preservation, maintenance and rehabilitation strategies. These performance models are usually monitored over time to establish the performance trend of existing infrastructure assets, eventually being used for budgeting future funding and resource allocation at the network level and Pavement Management Systems (PMS). The literature reports that repair and rehabilitation are important decisions for sustaining the serviceability and safety of civil infrastructure (Hegazy, Rashedi and Abdelbaset 2012). In the situation of competing treatment alternatives and limited resources, performance measures help to efficiently allocate the available resources to road networks (Stantec Consulting 2011) and (Haas, Abd El Halim, et al. 2012). On the other hand, performance measure models are also currently used at the project level to evaluate different rehabilitation strategies and select the best strategy that meets design criteria.

1.2 RESEARCH MOTIVATION

With the introduction of the new Mechanistic Empirical Pavement Design Guide (MEPDG) in 2004, new performance models have been introduced that have been developed solely based on the mechanistic empirical concept (Applied Research Associates 2004). Fundamentally, it is expected that a pavement will deteriorate at the same rate and level regardless of how it is being evaluated within the programing framework scheme. However, project level Mechanistic-Empirical (M-E) models have shown different performance and discrepancies in behavior compared to traditional models currently used in pavement management systems at the network level. This variation is expected due to the nature of each model, as well as the incorporation of other parameters into the M-E models. Since the M-E models are more representative of pavement asset performance, due to the incorporation of new parameters such as material properties, traffic characteristics and environmental impacts, there is a need to explore project level M-E models and investigate their suitability at the network level. It is vital to study the impact of these new evolved models on the budgeting and allocation strategies and determine their impact on rehabilitation selection through life cycle cost analysis.

1.3 SCOPE & OBJECTIVES

The objective of this research is to improve existing PMS prediction models and explore M-E model application at the project and network levels. Existing empirical models used in Canada by different agencies at the municipal level will be examined first. An attempt to enhance these models will be carried out, which will later be compared to the M-E Models. Pavement deterioration can be affected by a number of factors, including pavement age, traffic level, climatic effects and pavement structure (Li, Kazmierowski, et al. 2001). Historical performance data will therefore be classified according to these parameters, which are known to greatly influence pavement performance. The impact of climate change on performance models will be investigated, and models for deferent climatic regions will be developed based on available municipal data. Next, an optimization technique will be utilized to calibrate M-E models to suit local environments and practice conditions in Canada at the municipal level. The enhanced empirical models will be compared against the calibrated M-E models for different conditions in Canada, and the possibility of using the calibrated

M-E Models at the network level will be investigated. Life cycle cost analysis will be carried out to explore the impact of modeling change on strategy selection. It should be noted that this research gives greater consideration to the suitability of M-E Models at Project and Network levels and their respective impact on planning and budgeting, rather than detailed analysis for MEPDG calibration and material properties and modeling. This research will also evaluate the impact of changing the performance models and how that affects network optimization and budgeting outcomes. Research objectives can be summarized as follows:

1. Review and identify gaps in existing empirical models used across Canada and define the key parameters that influence municipal pavement performance. Special attention will be given to climate change and its respective impact on performance.

2. Examine historical performance data and develop enhanced empirical models classified according to parameters identified in the first step.

3. Review current M-E models incorporated into the (MEPDG) design guide and use optimization to calibrate the models to various municipal traffic and climate conditions across Canada.

4. Develop a prototype decision-making framework at the project level to evaluate and compare the impact of model changes on maintenance, preservation, and rehabilitation treatment selection, as well as associated cost prediction through a detailed life cycle cost analysis.

5. Study the impact of model type changes on planning and budgeting at the network level framework.

1.4 RESEARCH HYPOTHESIS

The hypothesis for this research can be summarized as follows:

- This research will make use of advances in distress data collection by utilizing a comprehensive distress database to develop and enhance existing empirical models
- Limited research has been conducted to develop prediction models for local municipalities and cities, and it is therefore expected that industries and pavement practitioners will benefit from the outcomes of this research
- The database can be used to evaluate the impact of climate change on pavement performance
- Incorporating M-E models into the PMS can improve its capabilities to truly predict actual pavement performance, as well as its budgeting and allocation strategies
- Develop project level decision-support tool to assess engineers select best Rehab strategy

1.5 RESEARCH METHODOLOGY

Figure 1-1 outlines the proposed research methodology. Existing empirical models used in Canada at the municipal level will be reviewed, and historical data from different municipalities across Canada will be utilized to develop new models. Optimization techniques, local experience and expert knowledge will all be employed to enhance the empirical models developed. On the other hand, preliminary M-E models will be implemented for the same classes that were identified in the development of the empirical models. Local data will also be used to calibrate these models through the use of optimization techniques. In order to evaluate these new models, a prototype decision-making framework will be developed, and models change impact will be compared through a detailed life cycle cost analysis at the project level for different rehabilitation options. In addition, the impact of model changes on planning and budgeting will be validated through full implementation of pavement management systems at a network level of analysis.

1.6 THESIS ORGANIZATION

Chapter 1 includes research objectives and motivations, in addition to the scope of the research. Chapter 2 includes a literature review, which discusses state-of-the-art methods of pavement performance modeling for both empirical models and M-E models, and identifies the factors which have the most impact on pavement performance. Chapter 3 discusses existing empirical models used in Ontario, as well as possible enhancements to these models, achieved through the use of historical performance data and better experimental design to classify models based on traffic patterns, subgrade condition, pavement thickness and functional class. Chapter 4 summarizes the impact of climate and regional changes on pavement deterioration and how these can influence pavement performance. Data from Western Canada will be used to develop models for this region, and will be compared to those developed for Eastern Canada. Chapter 5 evaluates Ride Comfort Index (RCI) models further, and develops deterioration models for municipalities in Ontario based on M-E principles. M-E models in the MEPDG are calibrated using measured data collected in Ontario. The calibration process utilizes a fully automated and genetic algorithm optimization technique to find the optimum calibration coefficients that represent the Ontario data. Chapter 6 involves the development of a decision-making framework to compare the enhanced empirical models developed with the new M-E models at the project level of analysis. Chapter 7 involves the implementation of the decision support tool, comparing the results of its life cycle cost analysis for rehabilitation alternatives, based on the two deterioration models streams. Chapter 8 compares the two types of models at the network level analysis. Two budget scenarios, designed to maintain network condition at an overall pavement quality index score of 65, are implemented based on the two model streams. Comparison between the budget expenditures of each is demonstrated, and the Chapter discusses how the prediction models impact decision-making. Chapter 9 summarizes and concludes the outcomes of this research, considering how this work has contributed to advancing the state of the pavement industry, as well as making recommendations for future work.

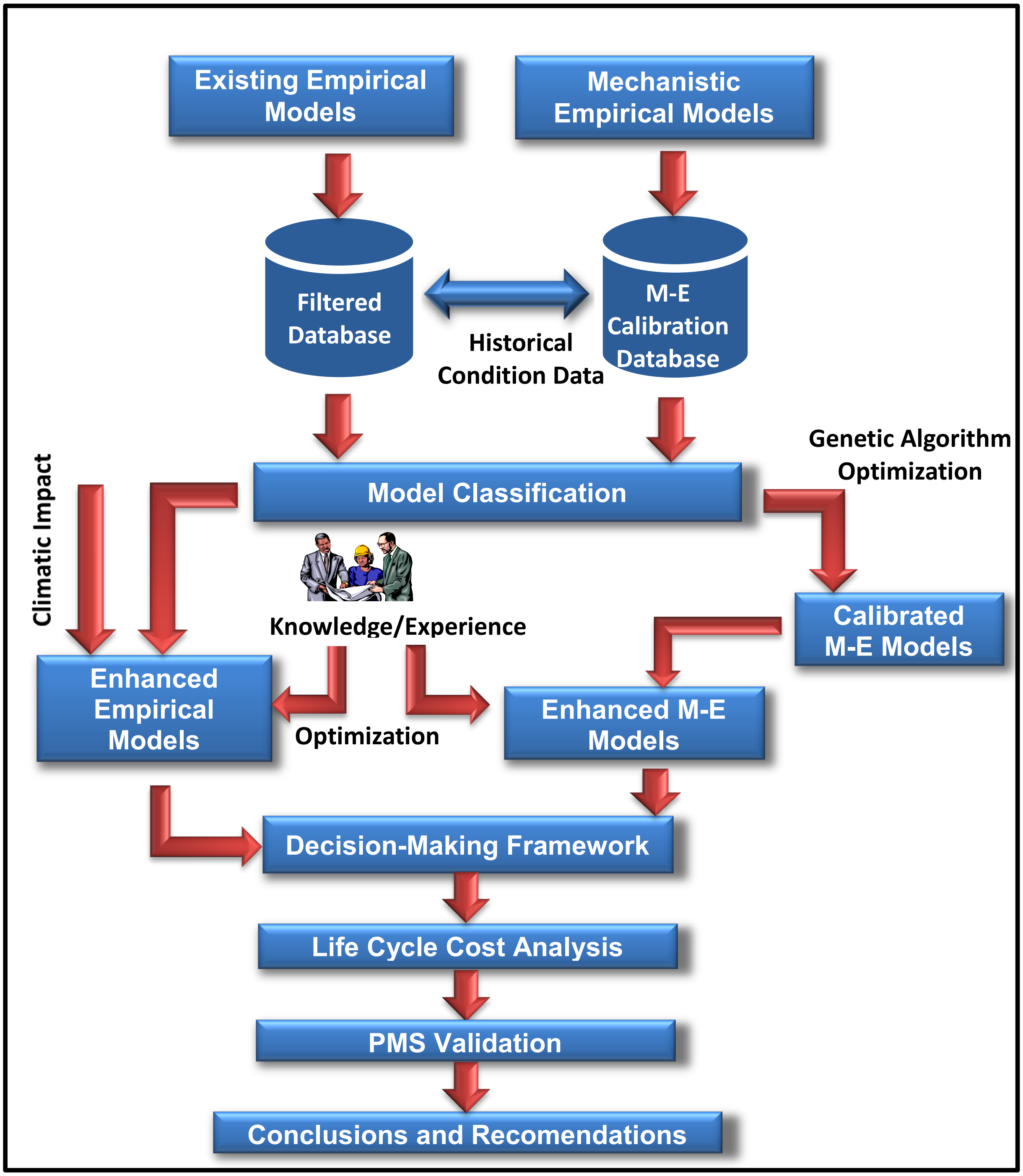


Figure 1-1: Research Methodology

2.0 Literature Review

2.1 INTRODUCTION

Pavement is one of the most essential elements of modern transportation infrastructure. Each year billions of dollars are spent on pavement maintenance and rehabilitation just to keep roads in functional service (TAC 2006). This annual investment has forced many transportation agencies to monitor factors affecting pavement performance, and to connect them to pavement behavior over the course of its service life (TAC 2013). Tracking such factors offers the advantage of accounting for their effects at the early stages of design and improving pavement's performance over its life cycle accordingly.

2.2 PERFORMANCE MODELS IN PAVEMENT MANAGEMENT SYSTEM

A logical approach that includes condition assessment, performance modeling, and alternative optimization is essential for the implementation of a Pavement Management System (PMS). An integral component of such an approach is pavement performance modeling that predicts future pavement conditions based on criteria such as traffic load, subgrade condition, and pavement thickness. The successful implementation of a PMS is dependent on how realistic these prediction models are, and whether they truly resemble actual pavement performance over time (Shahin 1994).

Traffic loading is expected to accelerate the deterioration of pavement, with the stress waves generated from moving traffic causing permanent deformation and increased crack propagation in the inner pavement layers. Climatic factors such as temperature, the freeze-thaw phenomenon, and moisture content will also accelerate crack propagation. The propagation of cracks into pavement layers allows water to penetrate into the pavement subgrade layer, further deteriorating its condition and eventually resulting in its failure to carry future traffic loads. A realistic prediction model should account for all expected parameters known to greatly influence pavement performance; however, due to the high complexity and interaction among these parameters, incorporating all of them into a prediction model is extremely difficult. Figure 2-1 illustrates the complexity of the performance prediction problem. The following subsection discusses some of those parameters that have been found to have a strong effect on pavement performance.

2.3 FACTORS IMPACTING PAVEMENT PERFORMANCE

2.3.1 Performance Concept:

Pavement performance is defined as the ability of a pavement to satisfactory serve traffic over time (AASHTO, 2003). Serviceability is defined as the ability of a pavement to serve the traffic for which it was designed for. Integrating both of these definitions yields a new and better understanding of pavement performance, which can be interpreted as the integration of serviceability over time (Yoder and Witczak 1975). Performance is a broad, general term describing how pavement conditions change or how pavement structures serve their intended functions with accumulating use.

Several methods have been developed to measure pavement performance. The Present Serviceability Index (PSI), measured on a scale 0 to 5, has been developed based on AASHO road test data. PSI was the first approach to be used for subjectively evaluating pavement performance. Later, the Pavement Condition Index (PCI), measured on a scale 0 to 100, was developed by the US Army Corps of Engineers as a quantitative measure for estimating pavement condition and performance (Shahin 1994).

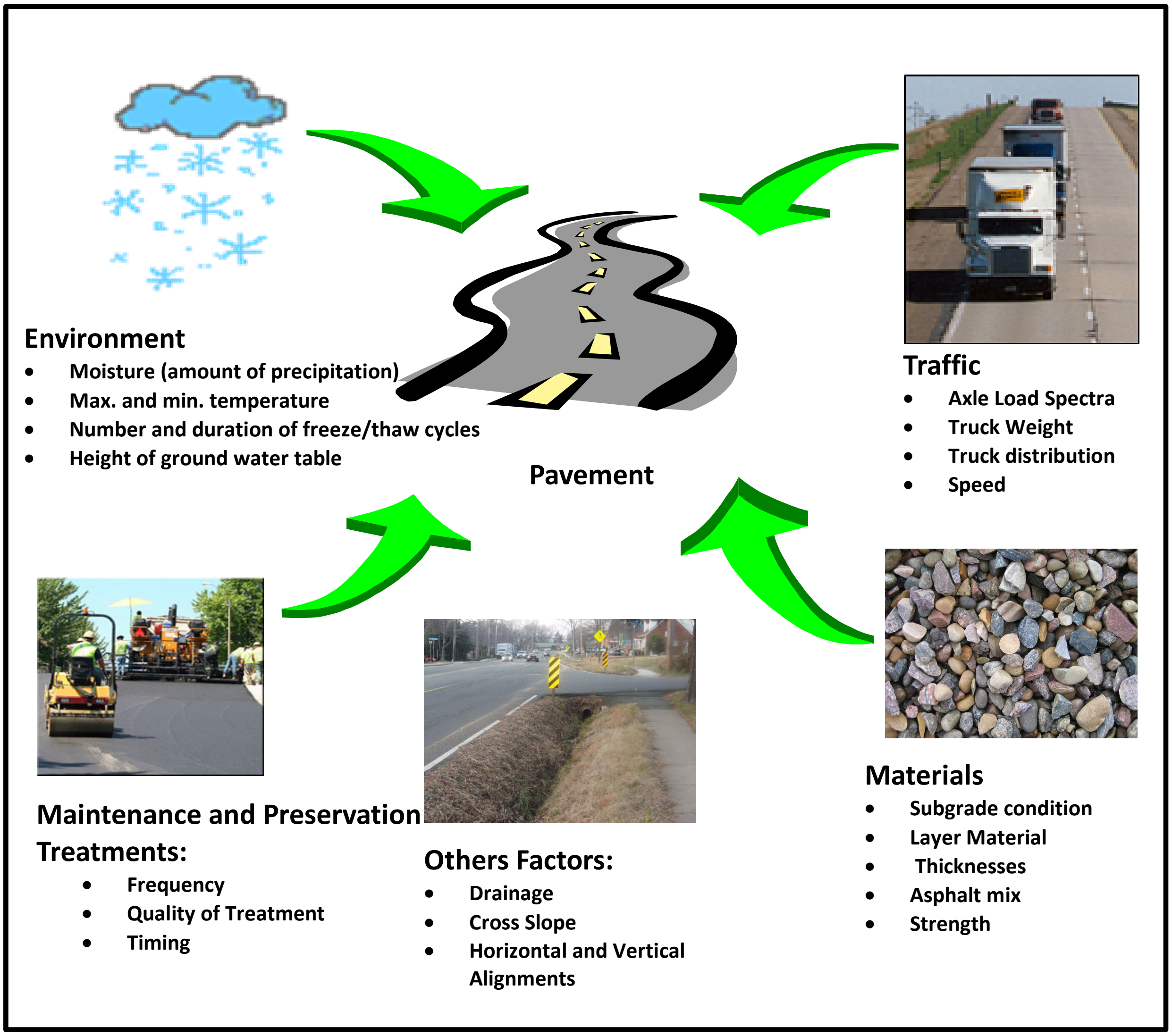


Figure 2-1: Factor Impacting Pavement Performance (Ayed, Helali and Zhghloul 2002)

Other methods such as the Pavement Condition Rating (PCR), also on a scale of 0 to 100 and the Pavement Quality Index, measured on a scale of 0 to 10 were also introduced as performance measuring approaches. In general, pavement performance depends on several factors, which can be grouped into the following categories, as noted below.

2.3.2 Environmental Impact on Pavement Performance

Several parameters have been identified as having a large impact on pavement performance. Seasonal variations of pavement material properties, such as temperature and in-situ moisture, have been shown to have a particularly strong effect on pavement performance. The fact that long term performance of a pavement structure is strongly dependent on subgrade soil and pavement layer properties makes any change in soil and pavement properties of great concern for long-term performance. This is particularly true in areas experiencing regular seasonal fluctuation in environmental conditions (Janno and Shepherd 2000). Nevertheless, climatic changes from region to region, combined with variation of site specific conditions, make it extremely difficult to develop prediction models that can fit in all regions. The need to develop regional prediction models is therefore an essential requirement for the design, planning and budgeting predictions of most transportation departments. The ability to predict regional environmental effects and incorporate seasonal variability of pavement materials into current design and planning procedures will greatly enhance pavement performance and reduce maintenance expenditures. Several environmental factors are reported to highly affect pavement strength and performance (Mrawira and Wile 2000). The most important of these include moisture content, the Ground Water Table (GWT), the freeze/thaw cycle and duration, and temperature, as illustrated in Figure 2-1. Seasonal variation in weather throughout the year plays an important role in changing the properties of pavement materials, which then in turn affect pavement stiffness and performance through secondary effects on the above named factors. Seasonal variation in weather produces changes in moisture content, GWT and the freeze/thaw periods throughout the year. These factors receive high consideration in current pavement research and design. The following section demonstrates the significance of these parameters by showing their impact on pavement in greater detail.

2.3.2.1 Moisture Content

Moisture content has a significant impact on the moduli of subgrades and unbound layers in some cases, which ultimately affecting pavement performance. A dramatic increase in water content (W/C) will result in a weakening of the unbound materials, while roadbed soils will reduce the modulus values of pavement layers, shortening the pavement service life and significantly increasing maintenance costs. Several studies have been conducted in the hope of establishing a relationship between moisture content and pavement strength (Janno and Shepherd 2000) and (Ksaibati, Armaghani and Fisher 2000). (Ovik, Birgisson and Newcomb 1999) carried out a study to investigate the relationship between climatic factors (including moisture content), surface and subsurface condition, and pavement material properties. The study confirmed that layer moduli vary with the state of moisture in the pavement. It was also shown that the seasonal distribution of the unfrozen volumetric moisture content in the base and subgrade layers is related to fluctuations in the stiffness of the layers.

2.3.2.2 Ground Water Table (G.W.T)

With pavement sites having a higher ground water table, water content becomes an important design concern. The existence of adjacent water tables plays an important role in increasing pavement moisture content when the water level become close enough to the pavement depth to cause a reduction in pavement life. To investigate the effect of GWT, (Ksaibati, Armaghani and Fisher 2000) performed a study on several Florida State Roads to evaluate decreases in base and subgrade layer strength as a result of proximity to the water table. The main objectives of this study were to correlate the depth of the water table to the pavement modulus values, which serve as an indicator of pavement performance, as well as to study the effect of high water tables on the moisture content of both the base course and the subgrade. The study showed that higher water tables result in higher base course and subgrade moisture content. Both Dynaflect and FWD showed that the water table had a significant impact on structural pavement performance. It should be noted that there were differences in the percentage increase in moisture content among different test sites. Despite such variation, the study conclusively demonstrated a high correlation between ground water table and moisture content.

2.3.2.3 Freeze/Thaw Phenomena

Pavement in seasonal frost areas experiences freeze-thaw cycles which expose its structure to significant moisture and temperature changes. These changes cause environmental fatigue in pavement, in addition to permanent fatigue due to vehicle traffic, both of which ultimately impact pavement performance over time. In an attempt to investigate this phenomenon, (Kestler and Truebe 2000) observed the relationship among moisture content and pavement layer moduli, focusing on the spring thaw period in Montana. As thawing began in early March, moisture sensors recorded a large, sharp increase in moisture content to levels well above those observed immediately prior to freezing. As thawing progressed, an equally rapid sequential decrease in moisture content was observed until a few days after thawing was complete, at which point the slope of the moisture content recovery curve significantly flattened. On the other hand, as thawing starts in early March, an apparent decrease in subgrade modulus occurs, until it reaches its minimum value at a thaw depth of 18”, at which point it starts to recover again as thawing depth increases, until thawing is complete. It should be noted that this recovery began at a deeper thawing depth in other test sites.

Another study (Janno and Shepherd 2000), noticed the same behavior for the base and subbase moisture content during the thawing period. This study was also carried out in Montana, and included 10 flexible pavement test sections. The study came to an interesting conclusion, finding that even though thawing officially started on March 30th, when temperatures reached 0°C, thaw-weakening actually started on March 20, based on moisture contents records. This indicates that predicting the start of thaw-weakening based on base temperature, for both base and subgrade, might in fact be misleading.

2.3.2.4 Temperature Impact

The structural performance of pavement is typically observed through the measurement and observation of pavement deflection. In flexible pavement, the surface deflection and layer moduli are significantly affected by the temperature of asphalt concrete, as the stiffness of the asphalt concrete layers dramatically influences its structural capacity. As the temperature of asphalt increases, the stiffness decreases, leaving it less able to withstand wheel load. A decrease in asphalt concrete stiffness results in higher stress being transmitted to the base and subgrade layers.

2.3.3 Traffic

Fatigue caused by traffic loading is one of the main parameters that shortens pavement life, causing tension at the bottom and compression at the top. Over time, these stresses result in the surface cracking, which allows for moisture to move through pavement sub layers (base and subgrade). Ultimately, repeated traffic loading over time will result in further cracking and pavement failure. Traffic volume, axle load, the number of equivalent single axle loads (ESAL's), tire pressure, truck type axles, configuration, load application time, and mechanism can be used to describe traffic-associated stresses on pavement. For this research, the functional classification (Arterial, Local or Collectors) in addition to traffic pattern for each road will be used to describe variation in traffic loading and volume. Data aggregation will be classified based on the functional traffic classes to develop empirical performance models and account for variation in traffic loading. Assumptions may be needed when detailed data are missing for M-E modeling to resemble the three traffic pattern for road functional classes.

2.3.4 Materials

Pavement layers used during construction play an important role in future pavement performance. The asphalt mix in particular should have good blending properties to resist cracking, while the base/subbase aggregate must have enough stiffness to resist deformation under repeated traffic. These desirable properties can be achieved through a properly performed compaction process. The subgrade resilient modulus is considered one of the important parameters used to describe pavement strength, since the subgrade is the foundation for all pavement structures. Good subgrade materials and condition will result in strong pavement with a long operational life. Several studies, such as (Tarefder, et al. 2008), have shown the importance of having a strong subgrade in order to increase pavement surface life. In this research, pavement performance models will be classified based on subgrade condition. The data used for model development will be aggregated to distinguish between performance models of weak subgrade pavement compared to strong subgrade pavement. It should be noted that it is not the intention of this study to investigate the impact of pavement material characteristics on the performance of prediction models; subgrade strength will instead only be employed as an overall parameter that describes pavement strength.

2.3.5 Other Parameters

Other parameters, such as geometric features (horizontal/vertical alignment, longitudinal and cross slope, provision of drainage facilities); design and construction factors, such as maintenance level and surface characteristics; and the quality of construction works, including initial roughness level and construction joints; are all known to impact pavement performance over time. Because these parameters generally have a small, indirect impact on pavement performance, they will therefore not be directly considered in the development and classification of the model.

2.3.6 Discussion

The previous literature review revealed that several parameters have been reported to highly affect the pavement performance. As shown in previous sections, moisture content, ground water table, temperature and freeze/thaw phenomena are highly correlated to pavement material properties. Previous studies have proved that those four environmental factors are strongly affecting the pavement performance. The previously mentioned parameters receive high consideration in current pavement design procedures and research development. The literature review also showed that the impact of seasonal variation on the pavement performance vary from one region to another. Some parameters may have significant impact in one region while they might have insignificant impact in other region. Models developed based on data collected from one region are valid only for similar environmental regions. The current research will develop new enhanced empirical models that account for factors that are found to highly affect the pavement performance. The following section will review some of the prediction models that have been developed in the past to predict future pavement condition or those are currently in use by transportations agencies.

2.4 TYPES OF PERFORMANCE MODELS

2.4.1 Empirical Models

The empirical modeling approach is based solely on the results of experiments or experience. Observations are used to establish correlations between the inputs and the outcomes of a process - e.g., pavement design and performance. These relationships are not directly measured, and instead involve engineering judgments such as expected trend directions and expected service life. Empirical approaches are often considered appropriate when it is too difficult to theoretically define the precise cause-and-effect relationships of a phenomenon. Most empirical models for pavement design purposes were developed at the project level rather than the network level analysis. The empirical based design method used by the American Association of State Highway and Transportation Officials (AASHTO 1993) is the most commonly used method for design. The AASTHO design equation is a regression relationship between the number of load cycles, pavement structural capacity, and performance, measured in terms of serviceability. The biggest disadvantage of this method is that its regression analysis has many limitations. As is the case for any empirical method, regression methods can be applied only to conditions similar to those for which they were developed. The AASHTO method, for example, has been adjusted several times over the years to incorporate extensive modifications based on theory and experience that allowed the design equation to be used under conditions other than those of the AASHO Road Test. Although these models can represent and explain the effects of specific factors on pavement performance, their limited consideration of materials and construction data results in wide scatter and many uncertainties. Their use as pavement design tools is therefore very limited (Schwartz and Carvalho 2008).

Several local attempts have been made to develop performance models at the network level of analysis that suit agency needs and requirements, mostly for the purpose of implementing pavement management systems. One examples of this is the development of performance prediction models for the state of Virginia (Sadek, Freeman and Demetsky 1995). In this study, data was compiled from annual condition surveys of Virginia's pavement network to develop prediction models for the interstate system. The study used regression techniques to select the significant predictors of deterioration. Another study based on the regression analysis was the development of prediction models for the state of Mississippi (George 2000), in which five pavement families are identified for model development: original flexible, overlaid flexible, composite, jointed concrete, and continuously reinforced concrete. Models for each family were developed for predicting distresses, roughness, and a composite condition index.

2.4.1.1 Types of Empirical Performance models

Various equations, mostly based on regression analysis, have been developed for predicting pavement performance. The usefulness of these empirical equations is limited by the scope of the database used in their development. These kinds of regression equations are valid only under certain conditions and should not be applied when actual conditions differ from these. These models can take the form of correlating one parameter that describes pavement condition, such as IRI or rutting, with other factors such as age or accumulated traffic over time. Such models are called distress-based performance models. On the other hand, performance models can also take the form of correlating the condition index to age or accumulated traffic, a process which is called an index-based model. This index could be an Overall Condition Index (OCI) or Pavement Quality Index (PQI), which is in turn driven by other indexes such as the Riding Comfort Index (RCI) or the Surface Distress Index (SDI) (TAC 2006).

2.4.1.2 HDM-4 Distress Models

The Highway Design and Maintenance Standards Model (HDM-III) developed by the World Bank has been used for over two decades to combine technical and economic evaluation of road projects, and to prepare road investment programs (Archondo-Callao 2004). The International Study of Highway Development and Management (ISOHDM) was later carried out to extend the scope of the HDM-III model, and to provide a harmonized systematic approach to road management, with adaptable and user-friendly software tools. This has produced the Highway Development and Management Tool (HDM-4). The HDM-4 is considered the successor to HDM-III, which has been used by various road agencies all over the world for the last 20 years.

HDM-4 includes a road deterioration framework, which provides a set of generic pavement condition deterioration models for various types of pavements. These generic models can then be calibrated to specific regions or countries in order to estimate pavement performance. HDM-4 includes models for predicting various types of distresses, including structural cracking, raveling, potholes, skid resistance, rutting, roughness and others. These models are available for both flexible and rigid paved roads, as well as surface treated, and unpaved roads. HDM-4 is typically used in cases of strategic planning of all roads managed by a road administration, or in cases of programming road works for roads in fair to poor condition (Archondo-Callao 2004). Several studies have been carried out using HDM-4 (Jorge and Ferreira 2012), (Jain and Parida 2005) and (Lea 1995) Due to its limited use for developed countries means the HDM-4 models cannot be used in North American regions, and as such they are out of the scope of this study.

2.4.2 Mechanistic Empirical (M-E) Models

M-E methods provide a technical improvement over empirical methods. The induced state of stress and strain in a pavement structure due to traffic loading and environmental conditions is better predicted using a theory of mechanics. Empirical models link these structural responses to distress predictions. Several studies over the past fifteen years have advanced M-E techniques, Including those conducted by the Departments of Transportation of Washington State (WSDOT), North Carolina (NCDOT) and Minnesota (MNDOT), to name just a few agencies that have developed their own M-E procedures. The NCHRP 1-37A project (NCHRP, 2004) delivered the most recent M-E-based method, which incorporated nationally calibrated models to predict distinct distresses induced by traffic load and environmental conditions. The NCHRP 1-37A methodology also incorporated vehicle class and load distributions in its design, a step forward from the Equivalent Single Axle Load (ESAL) approach used in the AASTHO design equation and other prior methods. The performance computation is done on a seasonal basis to incorporate the effects of climate conditions on the behavior of materials. Figure 2-2 shows the M-E process through the design cycle. The most important benefit of an M-E approach is its ability to accurately characterize in situ material conditions, including subgrade and existing pavement structures. This is typically measured by using a portable device such as Falling Weight Deflectometer (FWD) to measure actual field deflection on a pavement structure. These measurements can then be used to determine existing pavement structural support through backcalculation analysis to determine the approximate remaining pavement life. This allows for a more realistic design for the given conditions (Schwartz and Carvalho 2008).

One of the biggest disadvantages of the MEPDG analysis is its lack of consideration for pavement preservation. Pavement preservation provides a means for maintaining and improving the functional condition of an existing highway system and slowing deterioration. Although preservation is not expected to substantially increase structural capacity, it generally leads to improved pavement performance and longer service life and should therefore be considered in the pavement design process. However, the MEPDG procedure and related performance prediction models focus on new design and structural rehabilitation, and do not explicitly consider the contributions of pavement preservation treatments to overall pavement performance. There is a need to identify approaches for considering the effects of preservation on pavement performance and to develop procedures that facilitate consideration of pavement preservation treatments in the MEPDG analysis process (Li, et al. 2011). In this research, a life cycle cost analysis, which includes periodical preventive maintenance, will be used to compare empirical versus M-E models. In addition, using PMS data in the calibration of the MEPDG can produce inaccurate results. M-E Models were developed solely based on the LTPP data, which has a different data collection protocol compared to typical PMS data collection. Therefore, several considerations need to be accounted for when using the PMS data in the MEPDG calibration process (Mamlouk and Zapata 2010).

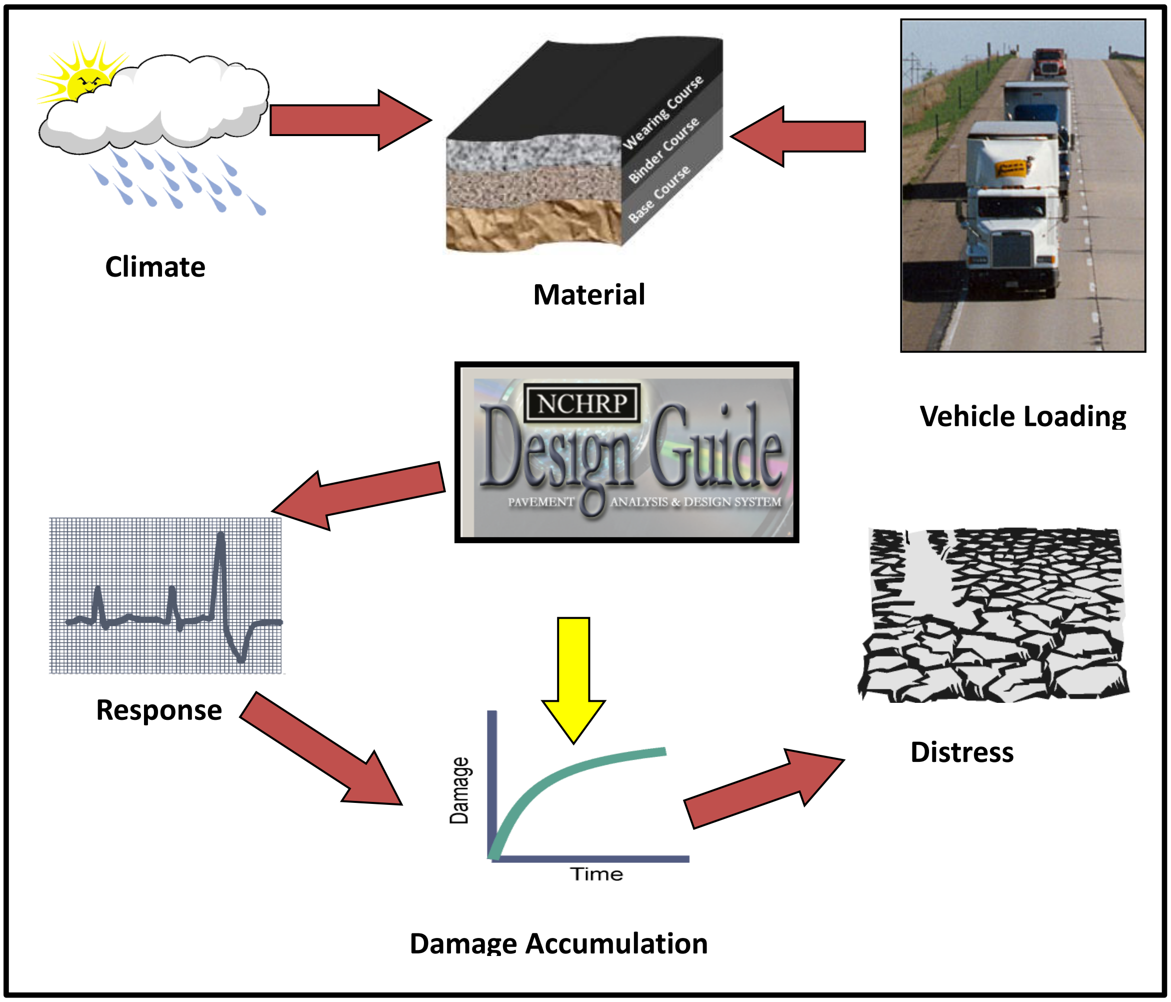


Figure 2-2: Mechanistic Empirical Process (Applied Research Associates 2004)

2.4.3 Experience Based Models

These experimental models are typically used in agencies without access to historical data to develop either deterministic or probabilistic models. These models are based on engineering experience, where serviceability loss or other measure(s) of deterioration vs. age are estimated for different combination of variables, typically using Markovian transition process models (N. Li 1997) or Bayesian models (Haas 2003) and (Haas and Kazmierowski 1998). Markov Modelling in particular was used in several studies, (Abaza 2016), (Mandiartha, et al. 2012), (Ortiz-Garcia, Costello and

Snaith 2006), (Reigle and Zaniewski 2002), (Pulugurta, Shao and Chou 2009), (Abaza, Ashur and Al-Khatib 2004), (Uchwat and Macleod 2012), (Butt, et al. 1987), (Haider, Chatti and Baladi 2011) and (MacLeod and Walsh 1999); however, these models usually do not account for factors impacting pavement performance such as climate or traffic, only considering experience and engineering judgment.

2.4.4 Artificial Intelligence Models

Several attempts have been made in the past to use artificial intelligence techniques in the development of pavement prediction models, using different algorithms such as Fuzzy and Gray Theories (Wang and Li 2011), (Jiang and Li 2005), (Li, Wang, et al. 2006), (Bianchini and Bandini 2010), (Pan, et al. 2011); and Artificial Neural Network (Lee, Ker and Liu 2014), (Kargah-Ostadi and Stoffels 2015). One study investigated the suitability of artificial intelligence techniques for pavement performance modeling, (Thube 2012) summarizing the implementation of a pavement condition prediction methodology using the Artificial Neural Network (ANN) to forecast cracking, raveling, rutting and roughness for Low Volume Roads in India. The study results suggest that ANN models satisfactorily forecast future individual distresses. (Yang, Lu and Gunaratne 2003) also implemented an overall pavement condition prediction methodology using ANN. In this study, three individual ANN models were developed to predict three key indices - crack rating, ride rating, and rut rating - used by the Florida Department of Transportation (FDOT) for pavement evaluation purposes. Results from this study suggested that ANN models have the capability to satisfactorily forecast the overall pavement condition index. The disadvantage of artificial intelligence models is that their forecasting is limited to only five years, which might not be practical for some agencies. Table 2-1 illustrates the main differences among various pavement performances models.

Table 2-1: Comparison among Different Pavement Performance Models

Model	Advantage	Disadvantage
Empirical	• More suitable for network level analysis • Simple to use • Tolerable estimation for short time forecasting	• Typically only addresses visual distress • More suitable for network level analysis • Only capable of predicting performance within its own development context • unreasonable estimate for long term performance forecasting • Only one climatic condition and one subgrade type were included in the case of AASHTO design guide • No Consideration for material properties
Mechanistic	• Always depends on mathematical engineering proof	• Only predict based on the mechanic of materials theory • Models could be away from real behavior because it is only based on pure mechanics • Do not account for other factors, rather than materials, that may impact pavement such as environment and traffic
Mechanistic-Empirical	• Can be used for both existing pavement rehabilitation and new pavement construction (Mechanistic-Empirical Pavement Design 2008) • It uses material properties that relate better to actual pavement performance • It provides more reliable performance predictions • It accommodates environmental, change in load type and aging effects on materials • It can better characterize materials allowing for better utilization of available materials, accommodation of new materials and an improved definition of existing layer properties	• Typically used at the project level • No consideration for periodical pavement preservation along pavement design life
Experience Based Models	• Suitable when no historical data is available	• Does not account for factors impacting pavement performance such as environment and traffic
Artificial Intelligence Models	• More suitable for short term forecast mainly at network level • Simple to use	• More site specific and does not account for material properties of the pavement

2.1 SUMMARY OF GAPS

A large number of factors have been identified as having a strong influence on pavement performance. These parameters are mainly site-specific and may vary from one region to another. In order to implement reliable models that can be used by pavement engineers and practitioners, model inputs should be simplified and easily quantified and obtained. In light of this, the current research prioritizes three parameters seen as having the greatest impacts on municipal roads in Canada: traffic, pavement thickness, and subgrade condition. Since traffic classification could vary between different municipalities due to different ways of classifying network data, therefore, it was essential to classify traffic patterns within each road functional class for different jurisdictions. Environmental effects will be considered through their impact on subgrade conditions and the comparison between pavement performances in eastern Canada region versus western Canada region. The total thickness of the pavement will be used to account for design, structural and maintenance impacts, while current research will be limited to the asphalt pavement type. The literature review showed that limited attempts have been carried out in the past to implement empirical or M-E models for network level analysis at municipal levels in Canada and United States. Limited work was done in the past, and the models developed are typically site-specific (Hein and Watt 2005), depending mainly on probabilistic models (Silva, et al. 2000) .

This research will develop reliable empirical models, based on condition data surveys collected from several Canadian municipalities over the past twenty years. It will also take into consideration changes in climate and traffic demands for Canadian cities. The current research will utilize modern automated data collection equipment that was not available in the past for most local agencies and municipalities. These new, more comprehensive models will be enhanced further through the incorporation of the M-E concept in model implantation. The next Chapter will develop empirical models that take into account factors that are highly affecting pavement performance.

3.0 Enhancement to Empirical Pavement Performance

3.1 INTRODUCTION

Developing the theoretical basis for this research requires an in-depth assessment of current municipal empirical models. Empirical performance models are generally being used in Canada within the framework of pavement management systems (PMS). Agencies such as municipal governments have been working locally to develop their own performance models for their unique local conditions. At the provincial level, the provincial ministries of transportation in Canada, such as the Ministry of Transportation of Ontario (MTO), have developed their own performance models based on historical pavement distress data, collected over more than two decades. However, limited efforts have been made at the municipal level to develop performance models. Along with decision trees, prediction models are being used to set the priorities for maintenance planning and budget allocations at the network level. Within a PMS, raw performance data is often converted to aggregated performance indices, such as RCI to quantify road roughness and SDI to quantify the extent and severity of surface distress.

3.2 CHALLENGES WITH EMPIRICAL MODELS

A review of the current practice within local agencies and municipalities in Ontario reveals that most municipalities have been using old performance models for decades in their pavement management systems. These models need to be revised and updated with the current practice of continuous distress data collection for each agency. A historical database with periodical condition data and/or pavement performance indices can be used as a source for the development of enhanced prediction models for these agencies. However, in some cases the database may suffer from missing and/or incomplete data. In addition, the historical performance data, the age of the pavement, or the date of the last major rehabilitation are required to develop a relationship between the performance data and the age of the pavement, which is almost always missing.

3.3 METHODOLOGY OF ASSESSMENT

This section provides the research methodology used to develop performance prediction models in the absence of original construction or rehabilitation data. Condition survey data from different Ontario municipalities over the past ten years will be utilized to develop these performance models. This data was collected from different municipalities in Ontario, mainly in the southern region. The models developed in this section will be specific for Ontario region while the next chapter will be designated for Western Canada model development. In general, Ontario has four seasons: summer, fall, winter and spring. January is usually the coldest month of the year, while July is usually the warmest. The northern part of the province has longer and colder winters compared to Southern Ontario. While the summer season can be very hot and humid, with daytime temperatures varying between 20°C and 30°C, winter is cold, with frequent snow and daily and nightly temperatures often below 0°C in most of the province. Spring is a rainy season in most parts of Ontario. During the fall, the weather gets cooler and the days get shorter. The early part of fall is rainy in some parts of Ontario, while In some northern parts of Ontario, it may start snowing in October.

During the course of reviewing the available data, it was noticed that it lacked the historical information necessary to accurately determine when it was last rehabilitated. The models discussed herein will use the limited historical data available, accounting for different parameters such as pavement thickness, traffic, and subgrade classes (Ayed, Clark and Whiteley-Lagace 2010). The pavement construction dates, or age of the pavement, will be incorporated into the proposed model and will be constrained based on local experience and engineering judgment. A linear programming technique will be employed to develop the performance prediction models. The approach presented in this section can be expanded to incorporate additional parameters and can easily be adapted to different agencies based on their local experience. The models presented herein will be compared later at project and network level of analysis.

3.4 PERFORMANCE INDEXES IN ONTARIO

PMS has been used extensively by municipalities across Canada for the last two decades. As a result, many of these municipalities in Ontario have multiple years of performance data from condition surveys. The three most common performance data recorded for municipalities are roughness, distress, and deflection. The raw data is often converted to a Performance Indicator (PI), which is then used to qualify pavement performance. It is expected that the pavement will deteriorate over time, and that this deterioration can be modeled through the performance indicators. Due to the limited data collected for deflection, the following section will focus on development of empirical models based on roughness and distress data.

3.4.1 Riding Comfort index (RCI)

One of the primary operating characteristics of a road, at least from the user's perspective, is the roughness, which represents the traveling public's opinion of the smoothness. The negative consequences associated with pavements with poor ride characteristics include:

- Increased vehicle operating costs
- Increased fuel consumption
- Increased travel time

- Increased vehicle operator discomfort
- Potential for reduced safety (in extreme cases)

For years, many cities across Canada, have undertaken data collection surveys to record roughness and distress data across their road network. The literature review showed that previous studies attempted to develop deterioration models mainly at the state and provincial level using roughness data (Kargah-Ostadi and Stoffels 2015), (Xu, Bai and Sun 2014), (Nassiri, Shafiee and Bayat 2013) and (Chen and Zhang 2011).

The ride characteristics of pavement can be objectively measured by commercially available equipment, which measures the longitudinal profile of the pavement surface. Profile data is then used to calculate an International Roughness Index (IRI), reported at different intervals (typically 30-metre). Roughness measurements are correlated to an assessment of ride quality, as determined by the ratings of a group of representative users of the pavements. This ride quality indicator is the Riding Comfort Index (RCI). The IRI, and ultimately the RCI for the pavement section is then based on the RCI for all stations included in the section. Theoretically, the RCI can vary from 0 to 100, where 0 is considered an extremely rough surface and 100 is an extremely smooth surface. However, a realistic minimum would be in the range of 20 to 40, with a value of 20 representing the need for complete reconstruction.

3.4.2 Surface Distress Index (SDI)

The Surface Distress Index (SDI) is a measure of physical pavement cracking, deformation and surface defects, collectively referred to as distresses. This measure provides an excellent indicator of material deficiency, rate of deterioration, structural adequacy, and environmental and soil type problems. SDI is therefore a key indicator of pavement performance, which may be used to monitor the condition of the network. In the past, the only method of completing a pavement condition survey was to walk or drive down the road and collect data manually. With advancements in pavement technology, automated data collection vehicles are now used to more accurately and quickly collect this data (Chamorro, et al. 2010). Different types of distresses are rated in terms of their severity and extent. Similar to the roughness data, the distress data is recorded and summarized at different intervals, typically 30-metre stations within each section of the network. The distress ratings are then transformed into separate scales from 0 to 100 for each distress type, which are further combined using distress-specific weighting factors to generate an overall SDI for each station. A sectional SDI score is then computed based on these stational SDI scores. Examples of the distresses surveyed under this methodology are shown in Table 3-1, while Figure 3-1 represents a sample of manual distress survey form used to collect distress data.

Table 3-1: Different Types of Measured Distresses

Different Distress Types	
• Patching	• Alligator Cracking
• Rippling & Shoving	• Potholes
• Raveling/Streaking	• Block/Map Cracking
• Flushing & Bleeding	• Longitudinal Cracking
• Distortion	• Transverse Cracking
• Excessive Crown	• Wheel Track Rutting
• Progressive Edge Cracking	

The SDI can vary between 0 and 100. A value of 100 indicates that the pavement surface is free of surface defects. Normally, an SDI of 60 to 70 is viewed as the critical range. Scores above this range generally indicate that any distresses that might exist are not severe or extensive in nature, while a score below this range generally indicate that significant distresses exist on the section. A section with an SDI below this range may experience an accelerated deterioration of performance due to rapid ingress of moisture, rapid propagation of cracking, increased susceptibility to freeze/thaw cycles, or other factors.

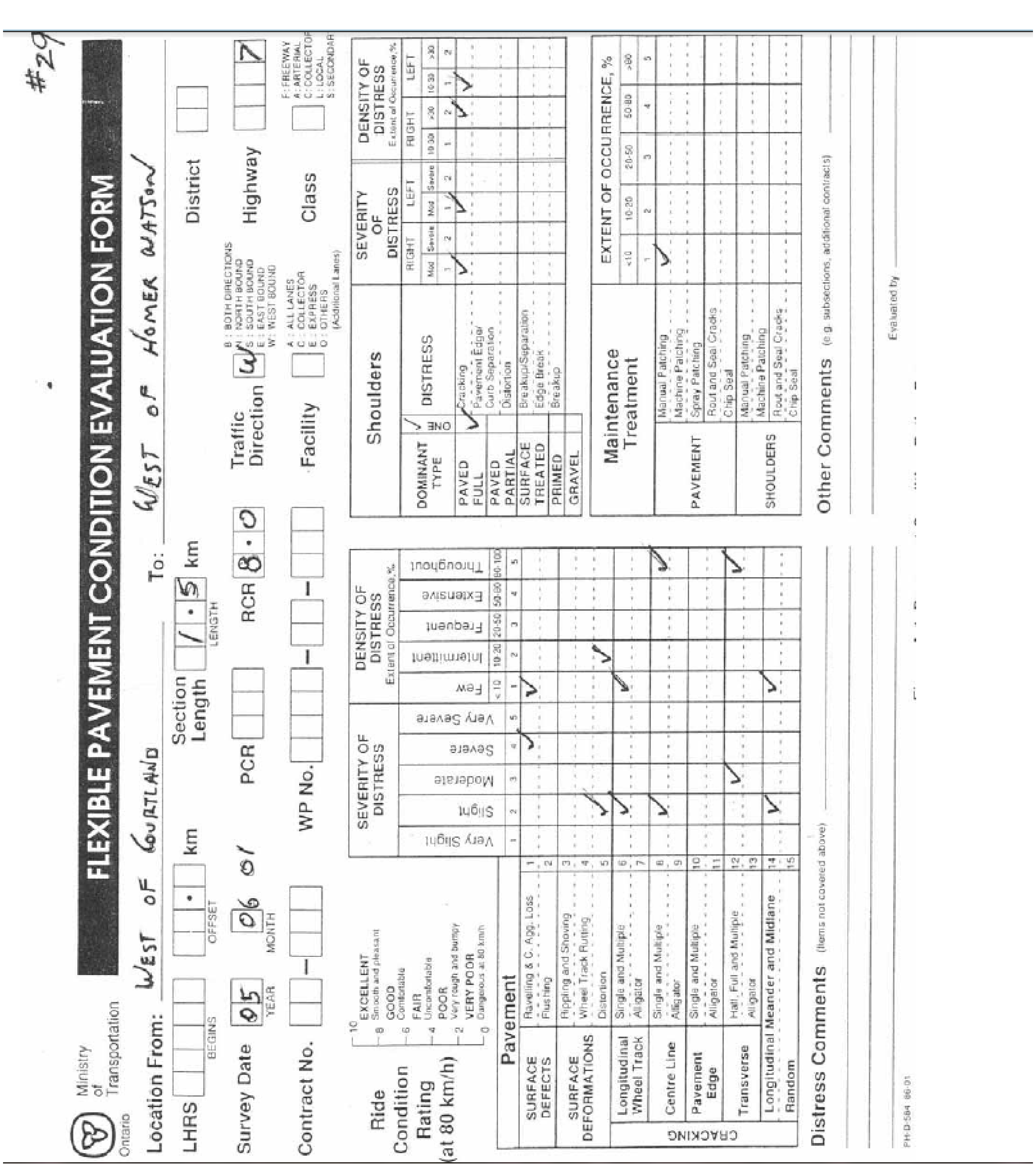


Figure 3-1: Sample Condition Evaluation Form for Flexible Pavement (Tighe, Capuruço and Jeffray 2006)

3.5 MODELING APPROACH

Several mathematical models have been used in the past to describe pavement performance at the network level (Karan, et al. 1983) and (Haas, Hudson and Zaniewsk 1994). These models varied from empirical, where a response parameter is related to structural or functional deterioration through regression, to subjective models where experience may be captured through a transition matrix such as the one used for Markovian models (Adedimila, Olutaiow and Kehinde 2009). This research uses a combination of experience based and optimization technique to develop deterioration models, which represent new evolved models based mainly on mathematical regression, and adopted through the use of local historical data and engineering experience.

A sigmoidal (i.e. S-shaped) form is adopted herein to describe pavement performance over time. This function is used widely in several pavement management systems to predict future condition of the pavement (Nassiri, Shafiee and Bayat 2013). This model form has a greater degree of flexibility in describing the deterioration of pavement performance, as it allows the models produced to be concave, convex, S-shaped, or almost linear. The following is the standard sigmoidal model form used in this study:

$$PI = O - e^{\left(A - B \cdot C^{\ln\left(\frac{1}{Age}\right)}\right)} \qquad \text{(Equation 3.1)}$$

Where,

- O = the initial condition of the pavement, immediately after rehabilitation (at age zero)
- PI = the performance index and could be the RCI or SDI parameter
- Age = the number of years since the last major rehabilitation or construction activity
- Coefficients A, B, and C are model parameters to be calibrated

Although it is expected that there may be some differences in the initial PI of the rehabilitated pavement section, based on the type and thickness of the rehabilitation activity, the initial condition (performance at age 0) for all rehabilitation activities was assumed to have the same value, which is the maximum possible PI value of 100, based on the assumption that a new surface is initially expected to be free of distress and have the highest ride comfort level. It should be noted that the RCI model, which converts IRI to RCI, has been locally calibrated such that a score of 100 represents an optimal or acceptable roughness level.

3.6 DATA AGGREGATION

The data used in this section was extracted from the PMS for various municipalities in Ontario, including Kitchener, London, and the Halton Region. This pavement management database contains historical data, collected over a span of almost two decades. Not all sections were surveyed during each data collection survey, and surveys were not collected on an annual basis. It is recommended that condition surveys for roughness and distress be collected at least every three years, with either one-third of the network being collected every year or on a recurring three-year basis for the entire network. As previously indicated, roughness and distress measurements are collected using automated data collection, and then converted into RCI and SDI scores. Table 3-2 shows the centerline lane lengths for sections used in the analysis for each city. These lengths are for flexible pavement types only. Table 3-3 shows the total number of sections that have been extracted from the different systems with observations. The table also indicates how many sections have records for each performance index, as well as the number of observations per section. For example, there are 16,691 sections that have RCI performance data, of which 2,149 sections have four years of RCI performance data.

Table 3-2: Sections Lengths

City	Length (KM)
Burlington	787
Halton Hills	444
Halton Region	361
Kitchener	715
London	1,676
Oakville	737
Richmond Hill	527
Waterloo	380
Grand Total	**5,628**

Table 3-3: Number of Sections with Observations by PI

PI	No. Sections with Observations	No. of Observations per Section					
		1	2	3	4	5	6
RCI	16,691	5,138	4,199	3,838	2,149	1,325	42
SDI	16,986	4	5152	4,430	3,870	2,190	1,296

In order to prepare a dataset that can be used for model development, several steps are needed to filter the data and remove outliers and unrealistic records. The first step is to remove sections that have only one observation, since they cannot be used to formulate a performance trend. As it is rare for sections to go for long periods without any treatment or rehabilitation, sections with two or more observations were further investigated and filtered out if the span between consecutive observations was too long. In addition, with the absence of any historical records regarding construction records, sections that do not have a deteriorating trend were removed from the dataset used for model development, as sections are expected to deteriorate over time. It is assumed that any increase in performance was the result of a rehabilitation-type activity.

3.7 MODEL DEVELOPMENT

3.7.1.1 Design of Experiment

In order to estimate future rehabilitation requirements of a pavement network, it is first necessary to formulate a series of performance curves that model both RCI and SDI. The rate of deterioration depends on many factors (Ayed, Helali and Zhghloul 2002), including, but not limited to:

- Environment/climate
- Pavement type
- Traffic volume
- Quality of materials used
- Construction quality
- Type of treatment strategy (e.g., overlay vs. reconstruction)
- Subgrade stiffness

It can be demonstrated, however, that the principal factors are traffic load, the properties and thickness of the pavement structure layers, and subgrade strength. There is therefore a need to develop deterioration models specific for each condition and class combination. For this study, three parameters were selected to classify the pavement condition:

- Thickness – three levels (thin, medium, thick) based on equivalent granular thickness (EGT)
- Traffic – three levels (low, medium, high) based on average annual daily traffic (AADT)
- Subgrade – two levels (weak, strong) based on local knowledge of soil properties

It was found that traffic classification could vary between different municipalities due to different ways of classifying network data, so it was essential to classify traffic patterns within each functional class within different jurisdictions. For example, medium traffic ranges in the Waterloo region could be different from medium traffic ranges in a higher traffic area such as Richmond Hill. The criteria used to reclassify traffic (AADT) and structural threshold levels (EGT) are shown in Table 3-4 and Table 3-5, respectively. The subgrade condition is based on subgrade resilient modules. These criteria are based on thresholds defined in the 1994 Pavement Design and Management Guide published by Transportation Canada (TAC 1994).

Table 3-4: Equivalent Granular Thickness (EGT) Classification

	EGT (mm) Classification		
Functional Class	**Thin**	**Med.**	**Thick**
Public Lanes - Residential	330	331 - 631	632
Public Lanes - Commercial	330	331 - 631	632
Locals – Residential	330	331 - 631	632
Locals - Indust/Comm	330	331 - 631	632
Collector – Residential	330	331 - 631	632
Collector - Indust/Comm	510	511 - 711	712
Arterials – Minor	510	511 - 711	712
Expressways	510	511 - 711	712
Arterials – Major	710	711 - 911	912
Freeways	710	711 - 911	912
Rural – Locals	330	331 - 631	632
Rural – Collectors	330	331 - 631	632
Rural – Arterials	510	511 - 711	712
Rural – Freeways	510	511 - 711	712

Table 3-6 shows the number of sections that have been considered in the model development for each combination of the three performance classes after data aggregation and filtering. The sections shown in Table 3-6 are only for the flexible pavement type, as these represent the vast majority of road networks.

Table 3-5: Traffic Classification

Functional Class	Typical AADT	Traffic Classification (AADT) Low	Med	High
Public Lanes - Residential	<500	250	251 - 499	500
Public Lanes - Commercial	<1,000	500	501 - 999	1,000
Locals - Residential	<1,000	500	501 - 999	1,000
Locals - Indust/Comm	<3,000	1,500	1,501 - 2,999	3,000
Collectors - Residential	<8,000	4,000	4,001 - 7,999	8,000
Collectors - Indust/Comm	1,000 - 12,000	1,000	1,001 - 11,999	12,000
Arterials – Minor	5,000 - 20,000	5,000	5,001 - 19,999	20,000
Arterials – Major	10,000 - 30,000	10,000	10,001 - 29,999	30,000
Expressways	>10,000	5,000	5,001 - 9,999	10,000
Freeways	>20,000	10,000	10,001 - 19,999	20,000
Rural – Locals	<1,000	500	501 - 999	1,000
Rural - Collectors	<5,000	2,500	2,501 - 4,999	5,000
Rural – Arterials	<12,000	6,000	6,001 - 11,999	12,000
Rural - Freeways	>8,000	4,000	4,001 - 7,999	8,000

Table 3-6: Number of Sections with Records for Model Performance Classes

Performance Indicator		Thickness	Subgrade	Traffic Low	Traffic Medium	Traffic High
Performance Indicator	RCI	Thin	Weak	3	5	8
			Strong	78	18	1
		Medium	Weak	125	136	452
			Strong	1,484	939	699
		Thick	Weak	331	192	196
			Strong	268	354	305
	SDI	Thin	Weak	0	5	4
			Strong	27	7	2
		Medium	Weak	97	91	56
			Strong	1,469	905	431
		Thick	Weak	300	256	742
			Strong	456	374	750

3.7.2 Expected Service Life

Service life is defined as the number of years between the implementation of the rehabilitation activity and the age at which the pavement condition reaches its rehabilitation trigger level. Three functional road classes were identified in this research: local, collector and arterial. Trigger values were established, as shown in Table 3-7. Once a PI reaches 60 for arterial roads, it is expected to undergo some form of major rehabilitation, such as a mill and overlay. In order to develop prediction models for each class combination shown in Table 3-6, an expected range of service life needs to be established in advance. This expected service life represents the incorporation of both experience and engineering judgment into the prediction models. It is expected that each road class will have a different life span, with the service life for the "average" condition for each functional class assumed at the values shown in Table 3-7. The average condition is defined as a flexible pavement with medium thickness, medium traffic, and strong subgrade. Under these conditions and characteristics, pavement will have a service life of 25 to 30 years before it will require a major rehabilitation, which is reasonable in a municipal environment especially on local low volume roads. Figure 3-2 shows trigger values for different road classes.

In order to predict the life span for other combinations, a reduction/increase factor was established for each combination, based on the average combination defined in Table 3-7. Table 3-8 shows the reduction/increase in factors used for each combination. It should be noted that these reductions/improvements in service life are based on experience and engineering judgment collected from serval transportation agencies, and as such could vary slightly among different agencies. These factors were applied to the life spans of each combination to develop the minimum and maximum life span for each functional class.

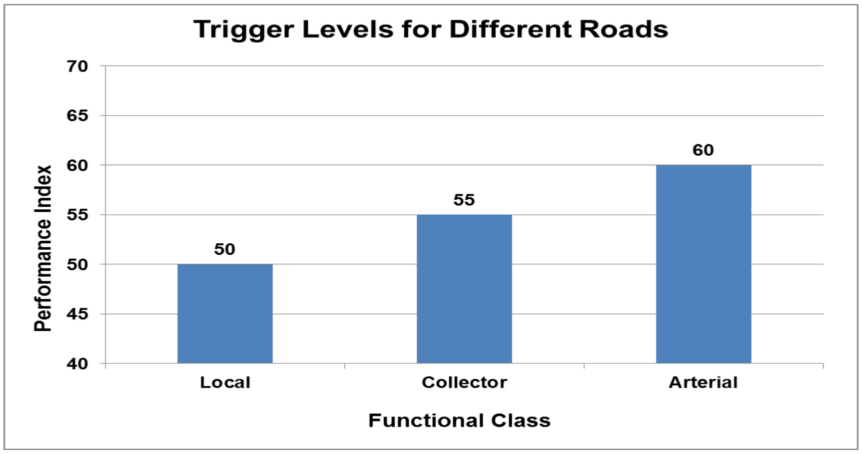


Figure 3-2: Trigger Levels for different Roads

As shown in Table 3-8, model 8 represents the average condition, with no reduction/increase for thickness, traffic and subgrade. Accordingly, different service lives for model combinations were estimated and referenced to the best condition, as shown in Table 3-9 to Table 3-11, respectively. It should be noted that these values for maximum and minimum expected service life are flexible and can be tailored to each agency's particular practice and needs. As shown in Table 3-9, thick asphalt with low traffic and strong subgrade will have an average life span between 33.1 to 39.7 years on a local road (model 13). At the other extreme, an asphalt section with a thin pavement structure, high traffic volume, and weak subgrade may require major rehabilitation as early as 12.6 to 15.2 years (Model 6), given that it has been under-designed based on traffic loading and subgrade strength. As compared to a typical design, this would essentially be considered a premature failure. It should be noted that the majority of sections fall in the "medium" range, as would be expected. However, service lives are developed for all cases, including the over-designed (best case) and under-designed (worst case) strategies.

Table 3-7: Trigger Values and Expected Life for Average Conditions

Functional class	Thickness	Traffic	Subgrade	Life (Years)		Trigger
				Min	Max	
Local	Medium	Medium	Strong	25	30	50
Collector	Medium	Medium	Strong	20	25	55
Arterial	Medium	Medium	Strong	15	20	60

Table 3-8: Reduction/Increase Factors for each Model Class Combination

Model ID	Thickness	Traffic	Subgrade	Reduction/Increase Factors		
1	Thin	Low	Strong	-15%	+15%	0
2	Thin	Medium	Strong	-15%	0	0
3	Thin	High	Strong	-15%	-15%	0
4	Thin	Low	Weak	-15%	+15%	-30%
5	Thin	Medium	Weak	-15%	0	-30%
6	Thin	High	Weak	-15%	-15%	-30%
7	Medium	Low	Strong	0	+15%	0
8	Medium	Medium	Strong	0	0	0
9	Medium	High	Strong	0	-15%	0
10	Medium	Low	Weak	0	+15%	-30%
11	Medium	Medium	Weak	0	0	-30%
12	Medium	High	Weak	0	-15%	-30%
13	Thick	Low	Strong	+15%	+15%	0
14	Thick	Medium	Strong	+15%	0	0
15	Thick	High	Strong	+15%	-15%	0
16	Thick	Low	Weak	+15%	+15%	-30%
17	Thick	Medium	Weak	+15%	0	-30%
18	Thick	High	Weak	+15%	-15%	-30%

Table 3-9: Expected Service Life for Each Model Class Combination (Local Roads)

Model ID	Thickness	Traffic	Subgrade	Expected Service Life (Years) to Reach Trigger Level of 50	
				Min	Max
1	Thin	Low	Strong	24.4	29.3
2	Thin	Medium	Strong	21.3	25.5
3	Thin	High	Strong	18.1	21.7
4	Thin	Low	Weak	17.1	20.5
5	Thin	Medium	Weak	14.9	17.9
6	Thin	High	Weak	12.6	15.2
7	Medium	Low	Strong	28.8	34.5
8	Medium	Medium	Strong	25.0	30.0
9	Medium	High	Strong	21.3	25.5
10	Medium	Low	Weak	20.1	24.2
11	Medium	Medium	Weak	17.5	21.0
12	Medium	High	Weak	14.9	17.9
13	Thick	Low	Strong	33.1	39.7
14	Thick	Medium	Strong	28.8	34.5
15	Thick	High	Strong	24.4	29.3
16	Thick	Low	Weak	23.1	27.8
17	Thick	Medium	Weak	20.1	24.2
18	Thick	High	Weak	17.1	20.5

Table 3-10: Expected Service Life for Each Model Class Combination (Collector Roads)

Model ID	Thickness	Traffic	Subgrade	Expected Service Life (Years) to Reach Trigger Level of 55	
				Min	Max
1	Thin	Low	Strong	19.6	24.4
2	Thin	Medium	Strong	17.0	21.3
3	Thin	High	Strong	14.5	18.1
4	Thin	Low	Weak	13.7	17.1
5	Thin	Medium	Weak	11.9	14.9
6	Thin	High	Weak	10.1	12.6
7	Medium	Low	Strong	23.0	28.8
8	Medium	Medium	Strong	20.0	25.0
9	Medium	High	Strong	17.0	21.3
10	Medium	Low	Weak	16.1	20.1
11	Medium	Medium	Weak	14.0	17.5
12	Medium	High	Weak	11.9	14.9
13	Thick	Low	Strong	26.5	33.1
14	Thick	Medium	Strong	23.0	28.8
15	Thick	High	Strong	19.6	24.4
16	Thick	Low	Weak	18.5	23.1
17	Thick	Medium	Weak	16.1	20.1
18	Thick	High	Weak	13.7	17.1

Table 3-11: Expected Service Life for Each Model Class Combination (Arterial Roads)

Model ID	Thickness	Traffic	Subgrade	Expected Service Life (Years) to Reach Trigger Level of 60	
				Min	Max
1	Thin	Low	Strong	14.7	19.6
2	Thin	Medium	Strong	12.8	17.0
3	Thin	High	Strong	10.8	14.5
4	Thin	Low	Weak	10.3	13.7
5	Thin	Medium	Weak	8.9	11.9
6	Thin	High	Weak	7.6	10.1
7	Medium	Low	Strong	17.3	23.0
8	Medium	Medium	Strong	15.0	20.0
9	Medium	High	Strong	12.8	17.0
10	Medium	Low	Weak	12.1	16.1
11	Medium	Medium	Weak	10.5	14.0
12	Medium	High	Weak	8.9	11.9
13	Thick	Low	Strong	19.8	26.5
14	Thick	Medium	Strong	17.3	23.0
15	Thick	High	Strong	14.7	19.6
16	Thick	Low	Weak	13.9	18.5
17	Thick	Medium	Weak	12.1	16.1
18	Thick	High	Weak	10.3	13.7

3.7.3 Model Implementation and Optimization

The coefficients A, B and C were used to produce a preliminary deterioration model, based on engineering judgment related to the initial performance of the pavement. For example, a newly constructed pavement would have a high RCI value for the first two years. Over time, as the pavement deteriorated, it would decrease at a higher rate. On the other hand, surface distress can be expected to start to develop within the first couple of years after rehabilitation. This step was performed for each section in the database. As previously indicated, the trigger level for major rehabilitation was assumed, as shown in Table 3-7, for all performance indices. Accordingly, it is expected that each of the 18 prediction models shown in Table 3-7 to Table 3-11 will reach the rehabilitation trigger level within the anticipated range of service life. The following factors were taken into consideration as much as possible during the optimization process:

1) Model Shapes

- SDI Models
    - Models are developed so that there is a shift horizontally to the left, such that there is an immediate decrease in performance within the first 2-3 years
    - The rate of deterioration should be gradual/slow from SDI 70 → 50
    - An inflexion point to be included at the tail end of the model (SDI at 30-40) such that the rate of deterioration increases at the end of the pavement's life
- RCI Models
    - May need inflexion point near the end if the model tails off to infinity

2) Model Order

- The relative order among models needs to be maintained, i.e., higher traffic deteriorates quicker than lighter traffic, thin pavement structure deteriorates quicker than thick pavement structure, and pavements with strong subgrade last longer than pavements with weak subgrade

These factors were taken into consideration through the application of additional constrains to the optimization process, on top of the existing constrains to produce the expected performance shape. The models also went through several trials with different additional constraints in order to produce the final expected shape. The next step was to calculate the error between the measured observations and predicted conditions, using the initial prediction model coefficients as shown in Figure 3-3. The least square error was calculated for each observation and summed for each section, as shown in the following equation:

$$\sum(PI_{Measured} - PI_{Predicted})^2 \quad \text{……………………(Equation 3.2)}$$

where $PI_{measured}$ is the measured value and $PI_{Predicted}$ is the predicted value at the same age. The least squares fitting is a mathematical procedure for finding the best-fitting curve to a given set of points by minimizing the sum of the squares of the offsets, or residuals, of the points from the curve (Weisstein 1995). Excel solver, which employs linear programming optimization techniques, was used to minimize the error between measured and predicted performance indices for each section. The optimization process was constrained so that expected service life for each section should fall within the expected range, as shown in Table 3-9 to Table 3-11. Other constraints were applied to coefficients A, B and C so that the developed model follows the expected shape. Figure 3-4 shows the final RCI model for one selected section from the database after running optimization procedures.

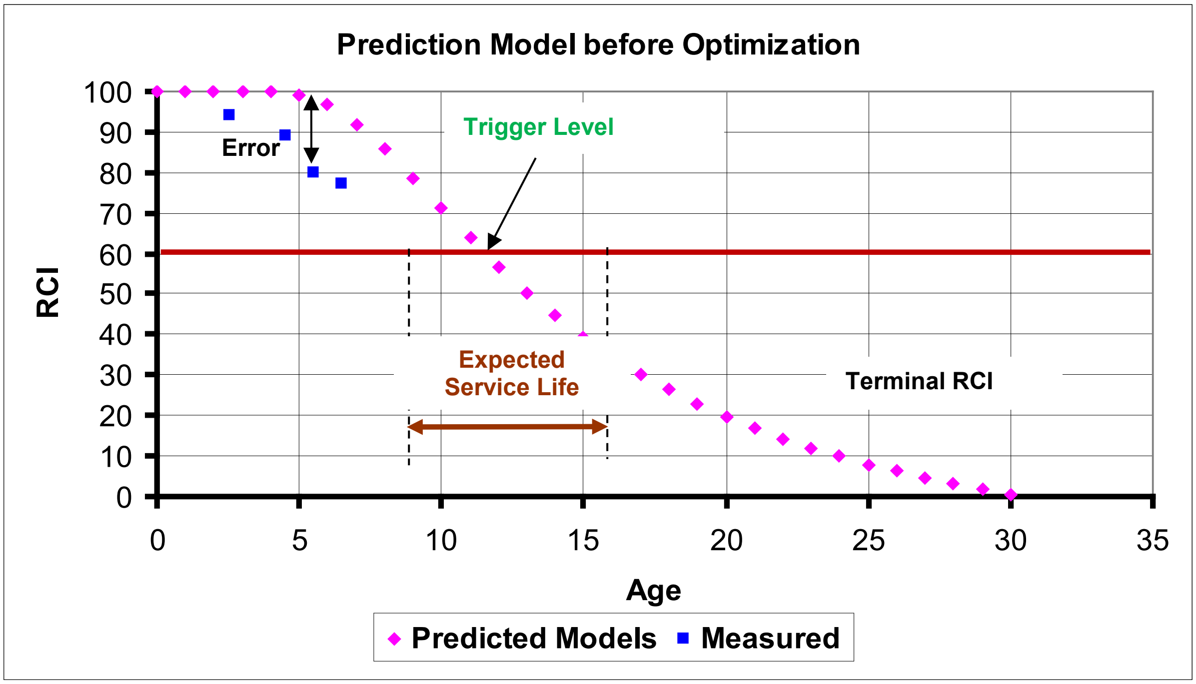


Figure 3-3: Prediction Models before Optimization

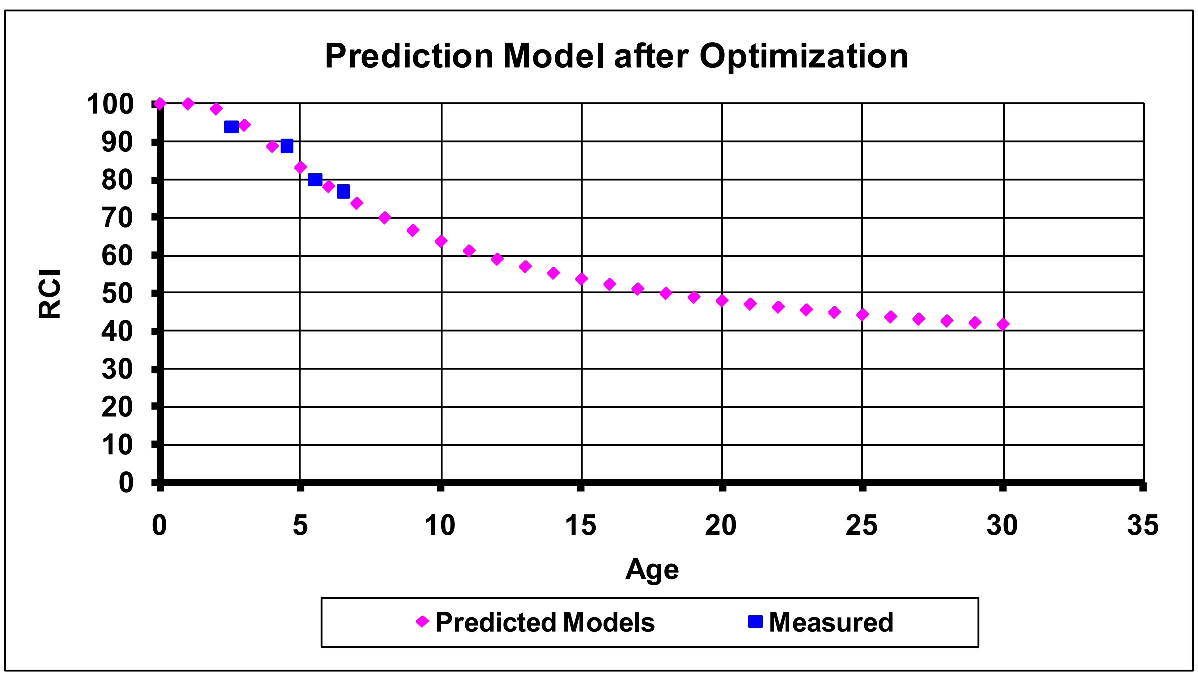


Figure 3-4: Prediction Models after Optimization

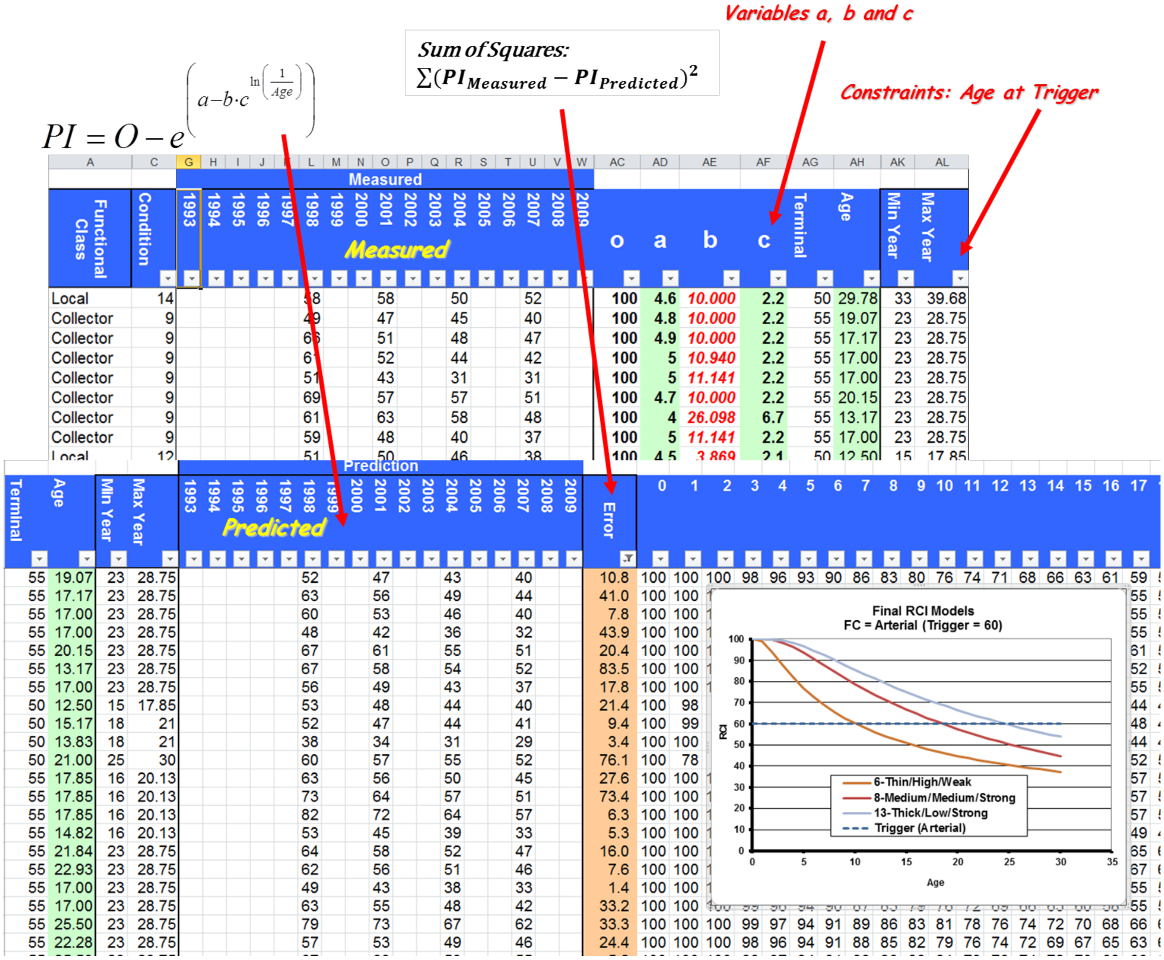


Figure 3-5: Modeling Optimization Process using Microsoft Excel Spreadsheet

Figure 3-5 shows how the optimization process was modeled using Microsoft excel spreadsheet. The graph shows how the measured data was grouped and constrained based on model condition index and how sigmoidal function was used to predict future condition using coefficients a, b and c. Microsoft Excel Solver was employed to minimize the difference between measured and predicted records by changing coefficients a, b and c while constraining the predicted service life (age) to be within the expected range.

3.7.4 Deterioration Model Results

Optimization to minimize error in prediction was applied for each section in the filtered database, with a value for the A, B and C coefficients obtained that best characterized the change in performance over the pavement life for each section. In addition, the coefficients were grouped and averaged for each model class combination. The previous steps were then applied to both performance indices presented in this study: RCI and SDI. Due to the lack of data near the end of the pavement life, the models resulted in performance classes not reaching the terminal value of 20 – the point at which total reconstruction is expected. As such, the models could be adjusted after the trigger level so that their rate of deterioration remained constant after the expected rehabilitation trigger level. A tangent can be drawn once the performance curve reached the terminal level. It should be noted that during PMS implementation process, it is not expected for a section to reach terminal level without receiving any kind of rehabilitation activity. Figure 3-6 summarizes the optimization process to implement the performance models.

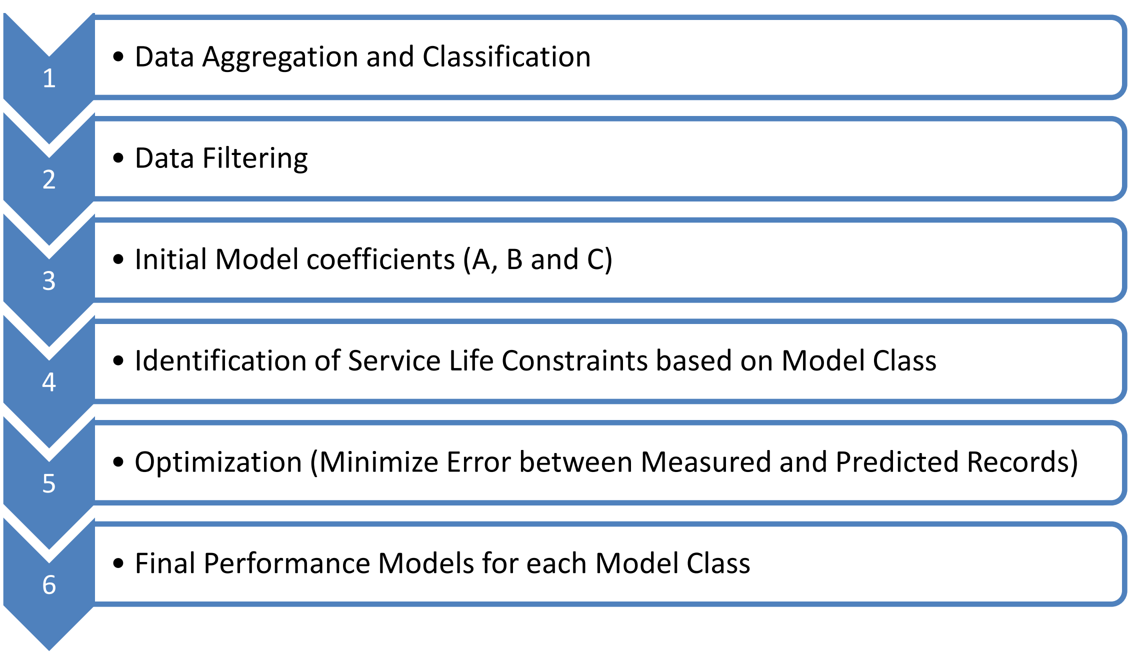


Figure 3-6: Data Aggregation and Optimization Process

Table 3-12: RCI Models Coefficients for Functional Classes

Model ID	Thickness	Traffic	Subgrade	RCI Model Coefficients											
				Local				Collector				Arterial			
				a	b	c	Age	a	b	c	Age	a	b	c	Age
1	Thin	Low	Strong	4.8	9.49	2.2	19	4.8	9.53	2.2	18	4.6	9.80	2.2	20
2	Thin	Med.	Strong	5.1	10.08	2.2	16	4.9	10.20	2.2	18	4.8	9.95	2.2	17
3	Thin	High	Strong	4 .8	10.0	2.2	22	NA	NA	NA	NA	NA	NA	NA	NA
4	Thin	Low	Weak	4.5	4.32	2.1	15	4.8	7.38	2.2	15	NA	NA	NA	NA
5	Thin	Med.	Weak	NA	NA	NA	NA	NA	NA	NA	NA	4.6	6.01	2.1	12
6	Thin	High	Weak	4.6	5.82	2.2	15	4.5	4.83	2.2	13	4.5	4.52	2.1	10
7	Med.	Low	Strong	4.8	10.21	2.2	23	4.8	10.89	2.2	23	4.7	11.82	2.2	22
8	Med.	Med.	Strong	4.7	11.2	2.2	28	4.8	11.2	2.2	23	4.7	10.06	2.2	19
9	Med.	High	Strong	4.9	9.57	2.2	18	4.9	10.06	2.2	17	4.8	9.98	2.2	17
10	Med.	Low	Weak	5.0	10.02	2.2	18	4.9	10.01	2.2	17	4.8	10.47	2.2	17
11	Med.	Med.	Weak	4.7	5.94	2.1	15	5.0	9.72	2.2	15	4.9	10.06	2.2	15
12	Med.	High	Weak	4.7	5.48	2.2	12	4.7	5.72	2.1	12	4.6	5.78	2.1	12
13	Thick	Low	Strong	4.6	10.62	2.2	34	4.7	12.49	2.2	29	4.7	12.11	2.2	25
14	Thick	Med.	Strong	4.9	11.46	2.2	23	4.7	10.72	2.2	24	4.7	11.81	2.2	22
15	Thick	High	Strong	4.9	10.59	2.2	21	4.8	10.56	2.2	20	4.7	10.69	2.2	19
16	Thick	Low	Weak	4.9	10.19	2.2	19	4.8	10.18	2.2	20	4.7	10.76	2.2	21
17	Thick	Med.	Weak	5.0	10.03	2.2	18	4.9	9.96	2.2	18	4.8	10.61	2.2	17
18	Thick	High	Weak	4.9	7.73	2.2	14	4.9	8.53	2.2	15	4.9	9.98	2.2	15

Note: NA refers to models where no enough data was available to produce models

Table 3-13: SDI Models Coefficients for Functional Classes

Model ID	Thickness	Traffic	Subgrade	SDI Model Coefficients											
				Local				Collector				Arterial			
				a	b	c	Age	a	b	c	Age	a	b	c	Age
1	Thin	Low	Strong	4.9	10.70	2.2	20	NA	NA	NA	NA	NA	NA	NA	NA
2	Thin	Med.	Strong	NA	NA	NA	NA	NA	NA	NA	NA	5.0	10.40	2.2	14
3	Thin	High	Strong	6.0	6.92	1.5	20	NA	NA	NA	NA	NA	NA	NA	NA
4	Thin	Low	Weak	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
5	Thin	Med.	Weak	NA	NA	NA	NA	NA	NA	NA	NA	5.0	9.60	2.2	12
6	Thin	High	Weak	6.0	5.93	1.5	14	6.0	5.61	1.5	10	NA	NA	NA	NA
7	Med.	Low	Strong	4.9	11.81	2.2	22	4.9	12.69	2.2	22	4.9	13.97	2.1	24
8	Med.	Med.	Strong	6.0	7.64	1.5	29	6.0	7.22	1.5	23	6.0	6.94	1.5	17
9	Med.	High	Strong	5.0	10.88	2.2	18	4.9	10.67	2.2	18	4.9	10.12	2.1	16
10	Med.	Low	Weak	5.0	10.44	2.2	18	5.0	10.80	2.2	17	4.9	11.30	2.2	18
11	Med.	Med.	Weak	5.0	9.26	2.2	15	5.0	10.10	2.2	15	5.0	10.23	2.2	14
12	Med.	High	Weak	5.0	7.95	2.2	12	5.0	8.74	2.2	12	NA	NA	NA	NA
13	Thick	Low	Strong	6.0	8.65	1.5	39	5.9	7.49	1.5	30	5.9	6.99	1.4	22
14	Thick	Med.	Strong	4.9	11.19	2.2	21	4.9	12.32	2.2	22	4.9	12.39	2.2	21
15	Thick	High	Strong	4.9	10.96	2.2	20	4.9	11.56	2.2	19	4.9	12.04	2.2	18
16	Thick	Low	Weak	5.0	1.89	2.2	21	5.0	11.86	2.2	20	4.9	11.27	2.2	17
17	Thick	Med.	Weak	5.0	10.53	2.2	18	4.9	10.65	2.2	18	4.8	10.13	2.1	17
18	Thick	High	Weak	5.0	9.03	2.2	15	5.0	9.93	2.2	15	4.9	10.24	2.2	15

Note: NA refers to models where no enough data was available to produce models

The coefficients for all models and functional classes are presented in Table 3-12 and Table 3-13. As can be seen in these tables, some of the model combinations did not have enough data to produce the models, while others did not meet the constraints for expected service life to maintain the expected trend for each combination. Model coefficients shown in Table 3-12 and Table 3-13 represent the best optimization results that can be reached with these constraints. It should be noted that coefficient B was sensitive to the second decimal point, while coefficients A and C were sensitive only to the first decimal point.

Close attention has been given to critical models to improve the optimization results, such as number of iteration and initial seeds, in order to meet all constraints and have the service life within the excepted ranges. These critical models were identified as follows:

- The most common municipal pavement condition, Model 8, with medium thickness, medium traffic, and strong subgrade
- The worst-case pavement strategy, Model 6, with thin thickness, high traffic, and weak subgrade. Close attention needs to be paid for any weak subgrade in Southern Ontario – it would be dealt with during the construction phase.
- The worst case pavement scenario for the strong subgrade, Model 3, with thin thickness, high traffic, and strong subgrade
- The best case pavement scenario, Model13, with thick thickness, low traffic and strong subgrade

These critical models can be used to build other case scenarios using relative relation among different conditions, especially in the absence of enough data. This research focuses mainly on the results of critical case scenarios, though models were generated for other conditions when data was available.

Figure 3-7 to Figure 3-12 show the final developed RCI and SDI models at each functional class for both RCI and SDI, respectively, after the optimization process. As shown in these figures, the critical models (Models 3, 6, 8 and 13) are only shown to avoid model overlap. These models are the ones that carry the most expected condition for each category. Although the optimization produced better results, interpolation between the two nearest combinations can be used to develop these missing models. The empirical models developed herein will be further investigated and compared with mechanistic- empirical models in the following Chapters.

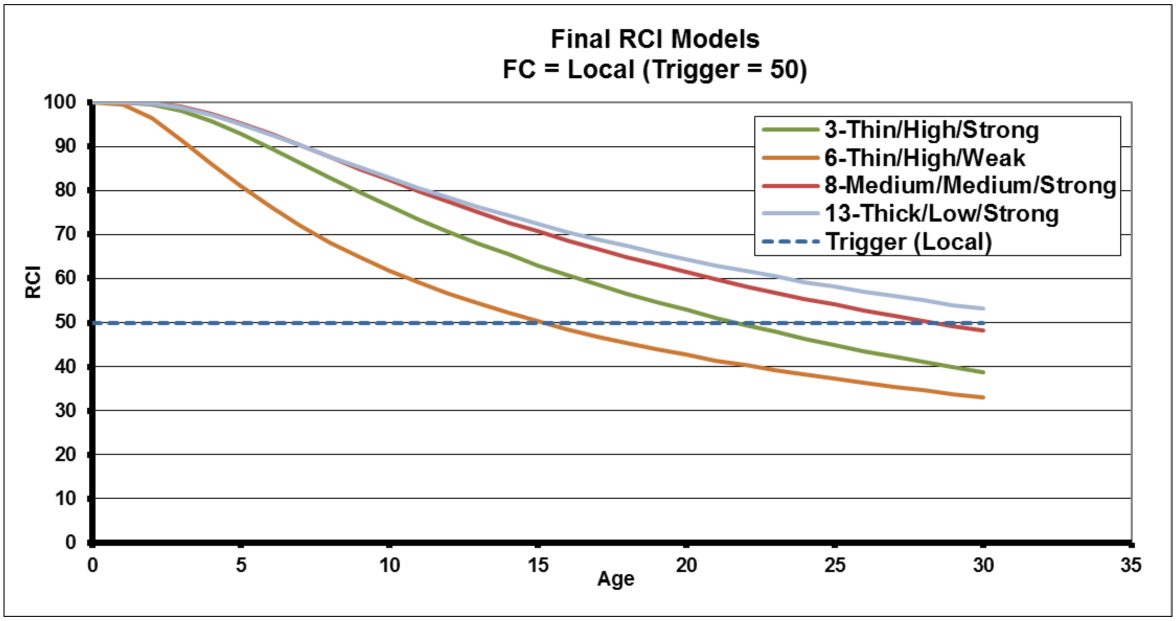


Figure 3-7: Final RCI Models for Critical Models (Local Roads)

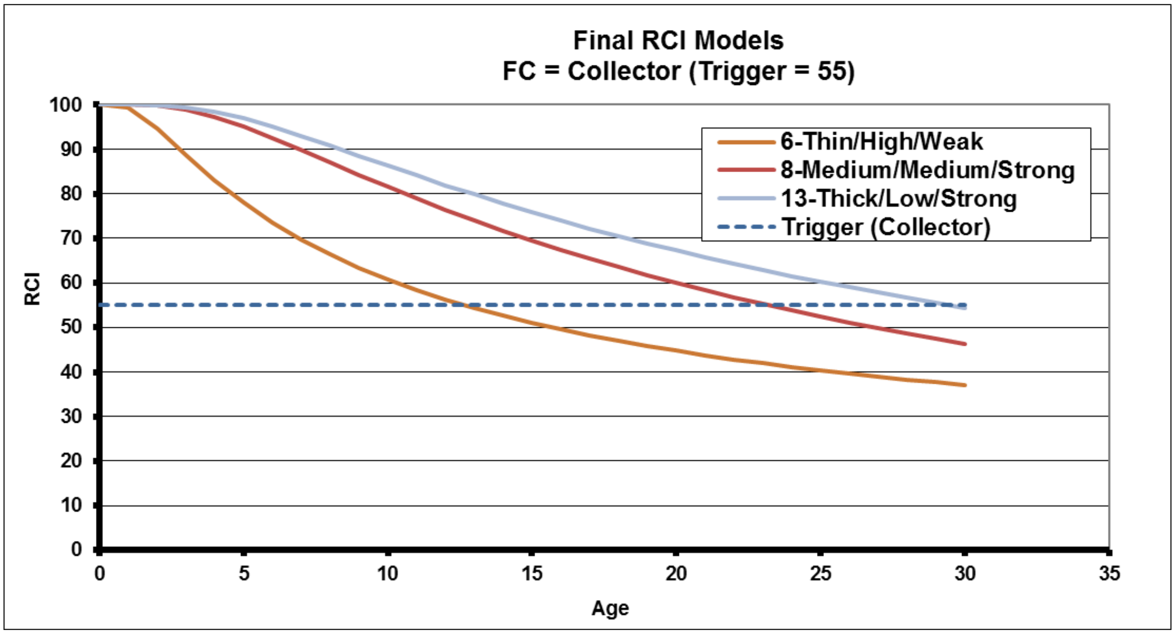


Figure 3-8: Final RCI Models for Critical Models (Collector Roads)

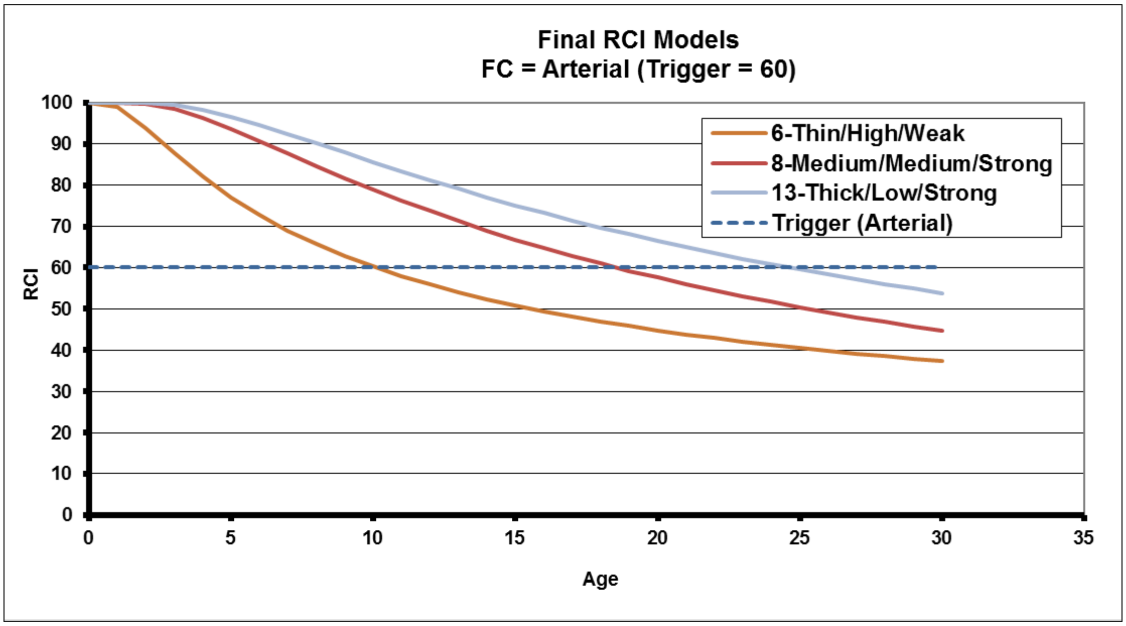


Figure 3-9: Final RCI Models for Critical Models (Arterial Roads)

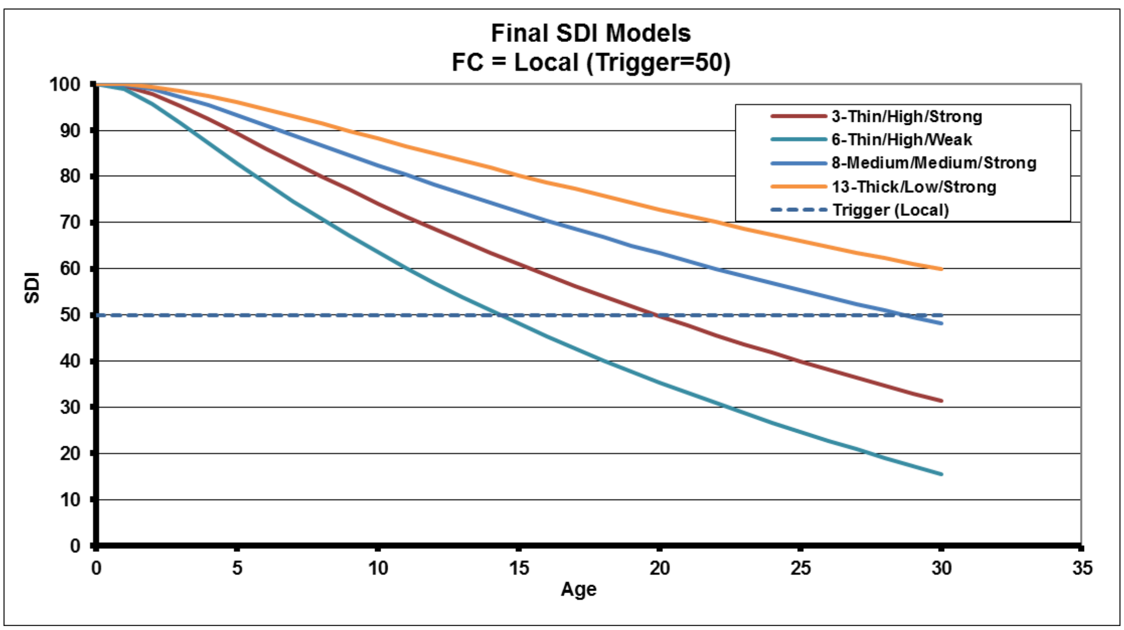


Figure 3-10: Final SDI Models for Critical Models (Local Roads)

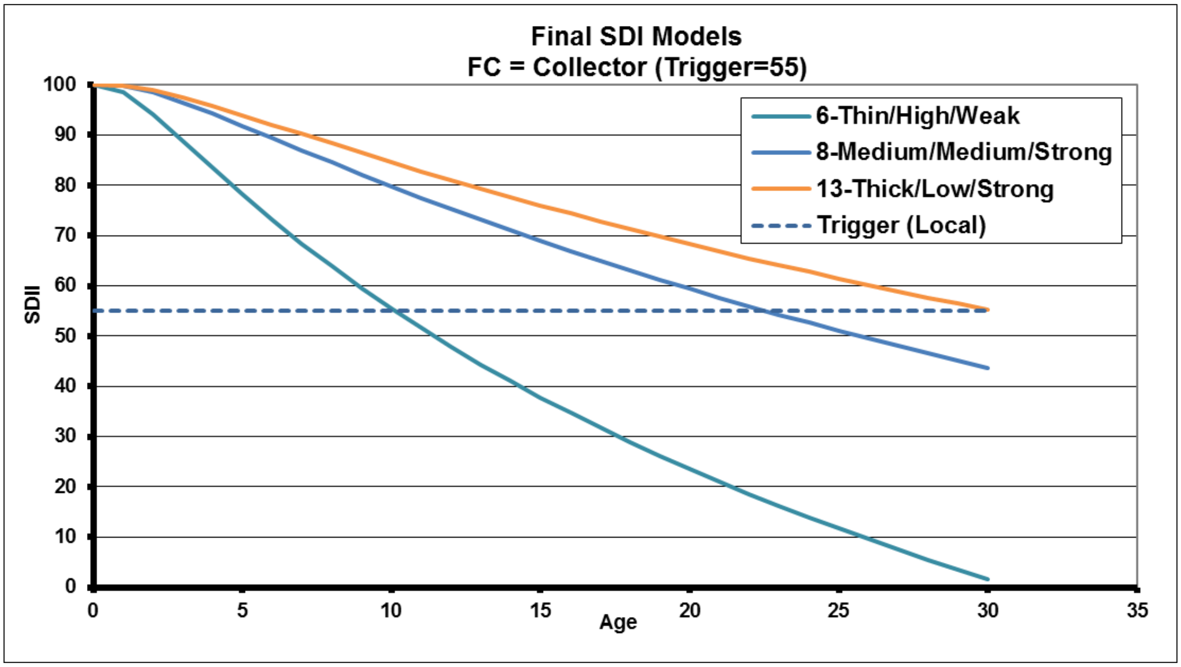


Figure 3-11: Final SDI Models for Critical Models (Collector Roads)

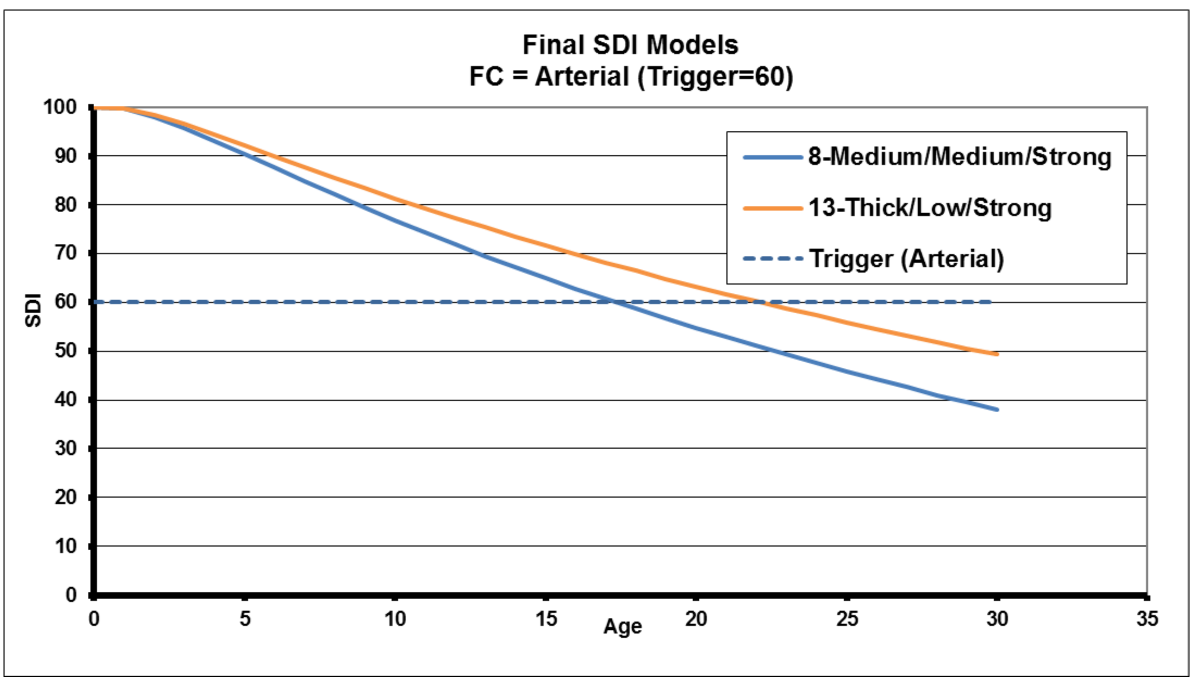


Figure 3-12: Final SDI Models for Critical Models (Arterial Roads)

Figure 3-13 to Figure 3-18 show the average predicted service life and expected service life range for all critical models. The graphs also show initial error in model prediction before optimization, as calculated from equation 3.2, as well as the final error after the optimization procedure. During optimization, there was a trade-off between minimizing the error in model prediction and meeting the service life target range. This was in addition to other constraints for expected model shape. Priority was giving to minimizing the error in model prediction. As can be seen in these graphs, all critical models met the expected service life within acceptable error tolerance; however, few other non-critical models did not meet the expected service life, since priority was given to reducing error in model prediction. The developed models for these scenarios represent the true performance of the pavement under this condition, using real measured data, regardless of the resulting service life after optimization.

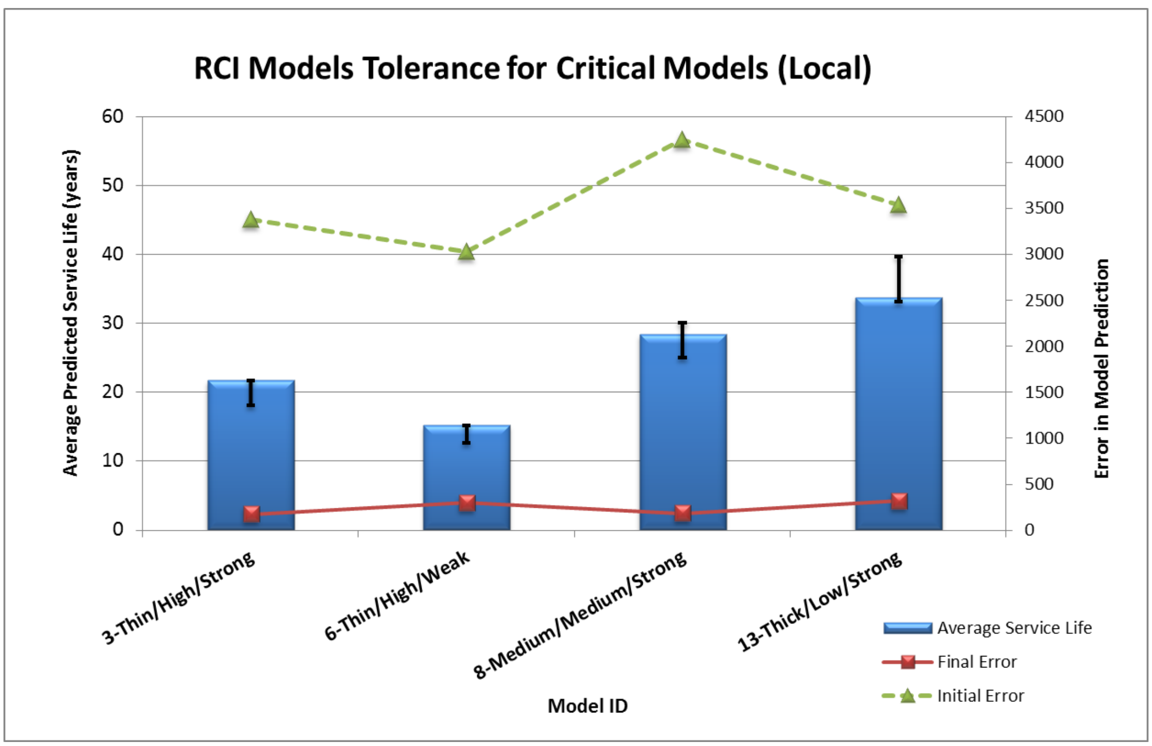


Figure 3-13: RCI Models Tolerance for Critical Models (Local Roads)

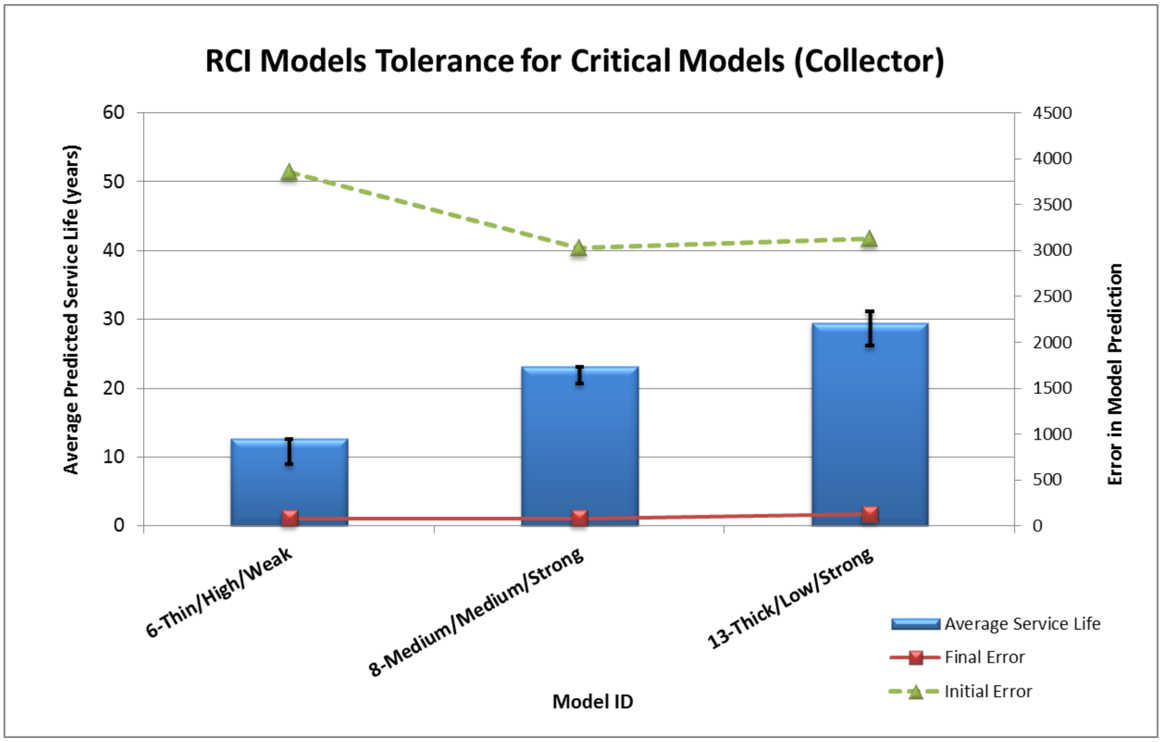


Figure 3-14: RCI Models Tolerance for Critical Models (Collector Roads)

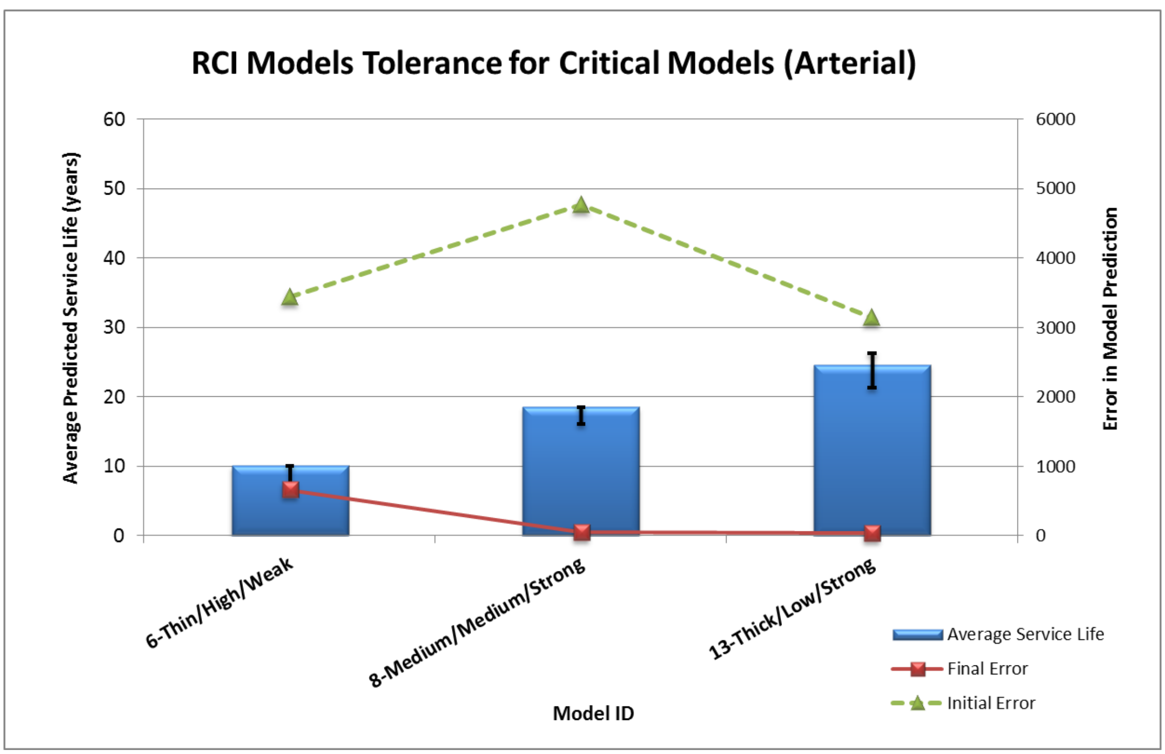


Figure 3-15: RCI Models Tolerance for Critical Models (Arterial Roads)

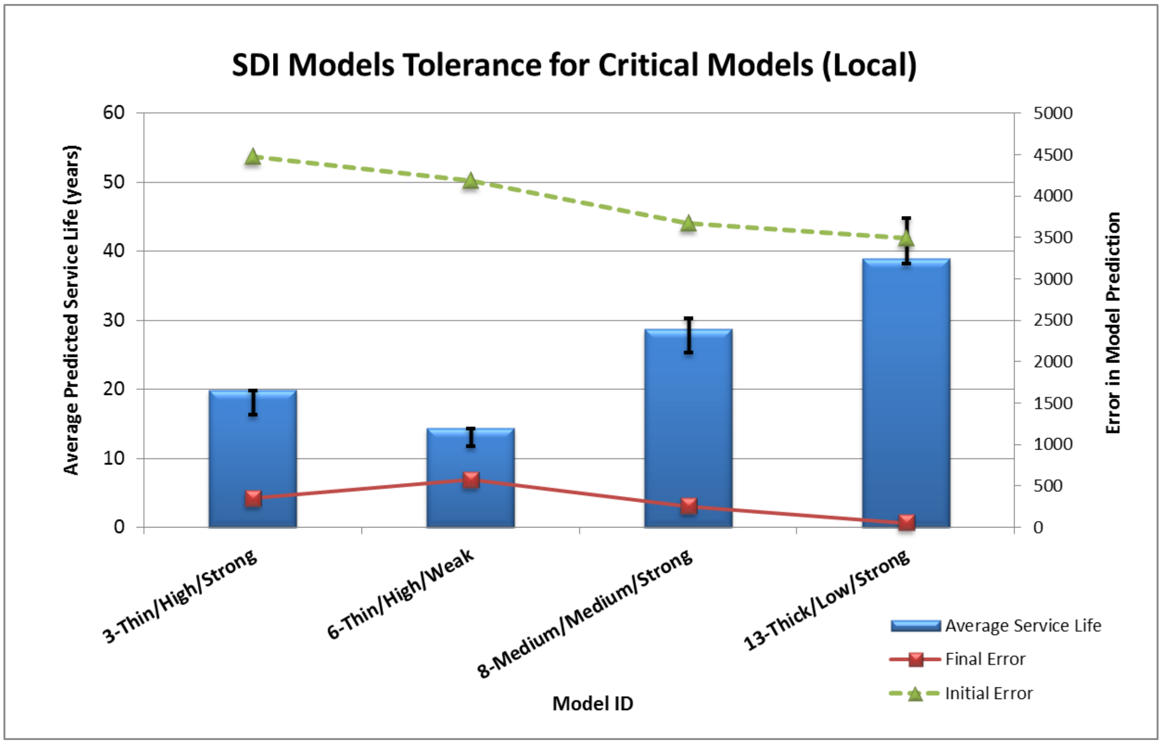


Figure 3-16: SDI Models Tolerance for Critical Models (Local Roads)

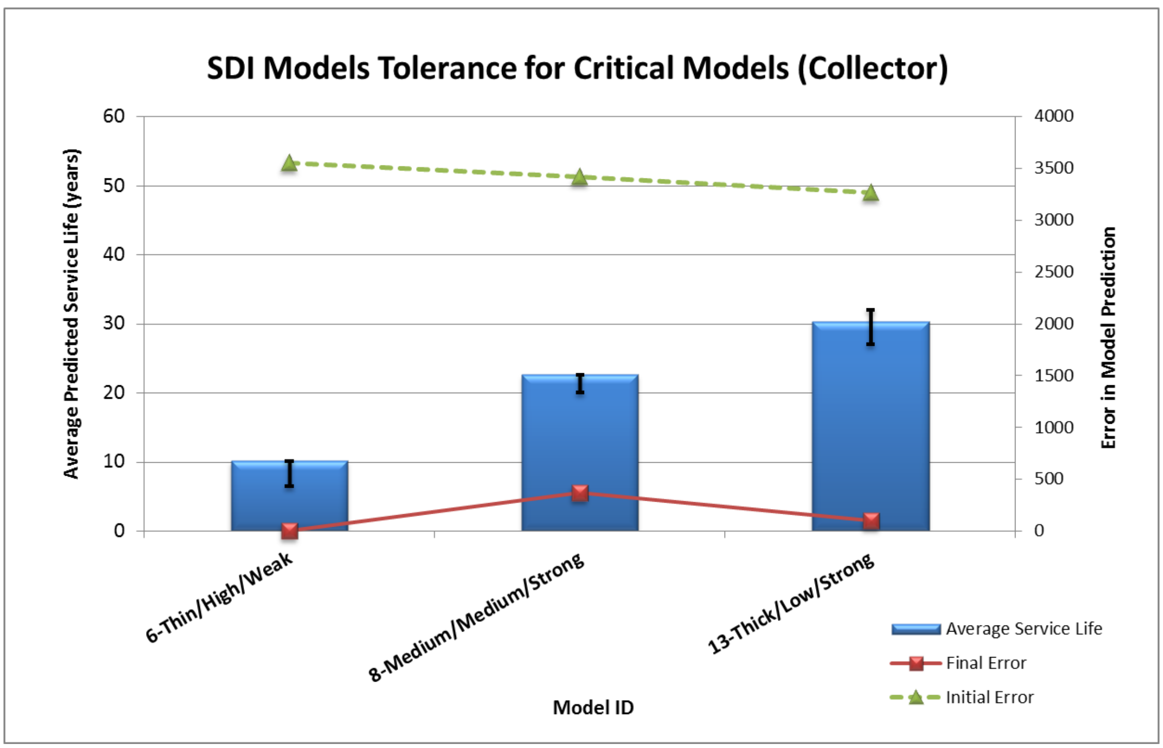


Figure 3-17: SDI Models Tolerance for Critical Models (Collector Roads)

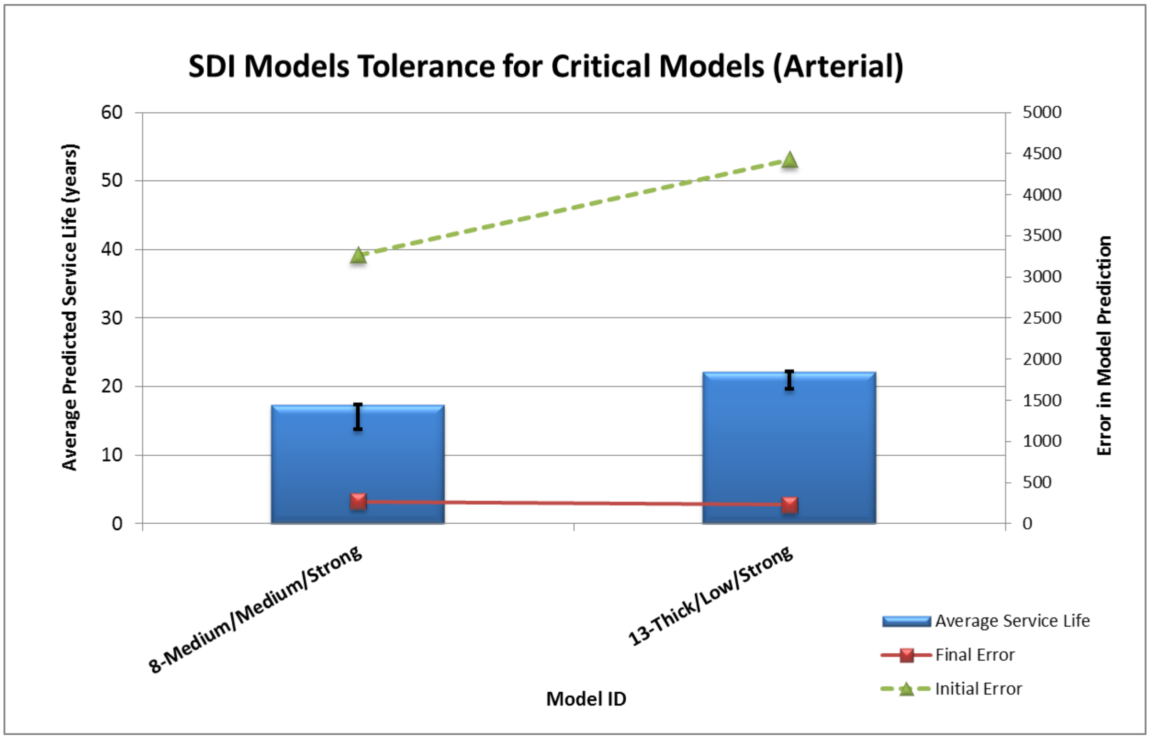


Figure 3-18: SDI Models Tolerance for Critical Models (Arterial Roads)

3.8 DISCUSSION

These prediction models are based on the assumption that the current performance classification is applicable to all historical records. In reality, there may be cases where traffic volumes have increased such that a particular section has moved from one performance class to another. However, filtering these sections from the analysis would further reduce the number of sections available for modeling. These cases are also important, as they are representative of the lower end of the service life range. In short, if a section has seen a significant increase in traffic volume, it will likely have a higher rate of deterioration, thereby falling within the lower end of the service life range. It is important to note that prediction models are intended to represent "average" or "typical" conditions. Prediction models are not representative of either the super-achievers (pavements that far exceed their expected service life) or the premature failures, which are often due to construction or material quality issues. However, it is notable that pavement design needs to account for changes that occur as a result of changes in climate or traffic loads. Due to the sections being classified into different performance classes, these prediction models can easily be expanded to include other factors, such as climate or environmental zones, as well as to include other performance indicators or other performance data stored within the PMS.

An integral part of the model development is the PMS itself, or, to be more specific, how well it is maintained and how often its data is collected and/or updated. If data is not captured in the database, it obviously cannot be captured in the modeling. The enhanced prediction models in this section will be compared against M-E models at the project and network levels to identify the impact of the transition from empirical models to M-E models on strategy selections and budgeting.

3.9 MODEL VALIDATION

To determine the quality of the developed models, it is essential to quantify and report the predictive validity of the derived models. The model validation should be conducted based on data collected from sections that were not used in the model development. As mentioned before in section 3.6, sections with no overall deterioration trend were excluded from the study. These sections were excluded because they had more than three observations but with no overall deterioration trend, however, consecutive deteriorating points in these sections until next peak observation can be used to verify the developed models. Therefore, one section for each critical condition was identified to verify the developed models. In some cases, the subset for each condition was not large enough to find a suitable section for model validation due to large gaps between observations, unrealistic deterioration trend or limited number of sections. Therefore, only critical conditions with sections contain reasonable observations were included in model validation process. Figure 3-19 to Figure 3-24 show the comparison between predicting condition indexes using initial model coefficients before the optimization and after the optimization. Figure 3-19 to Figure 3-21 show improvement in RCI prediction for the selected sections for different functional classes. Figure 3-22 to Figure 3-24 show improvement in SDI prediction for the selected sections for different functional classes. The graphs show the least square error as calculated from equation 3.2 on a logarithmic scale. The graphs show the sum square error using the initial models coefficients before applying model optimization and after the use of final optimized models to predict the condition index. As shown in all sections selected for validation, the use of the new developed models showed a significant improvement in the model prediction and reduction in model errors as a result of using the new developed models. Condition 8 in particular received the highest reduction in model sum square error. The current analysis demonstrates that the developed empirical models herein have the capability to predict reliable future condition of pavement.

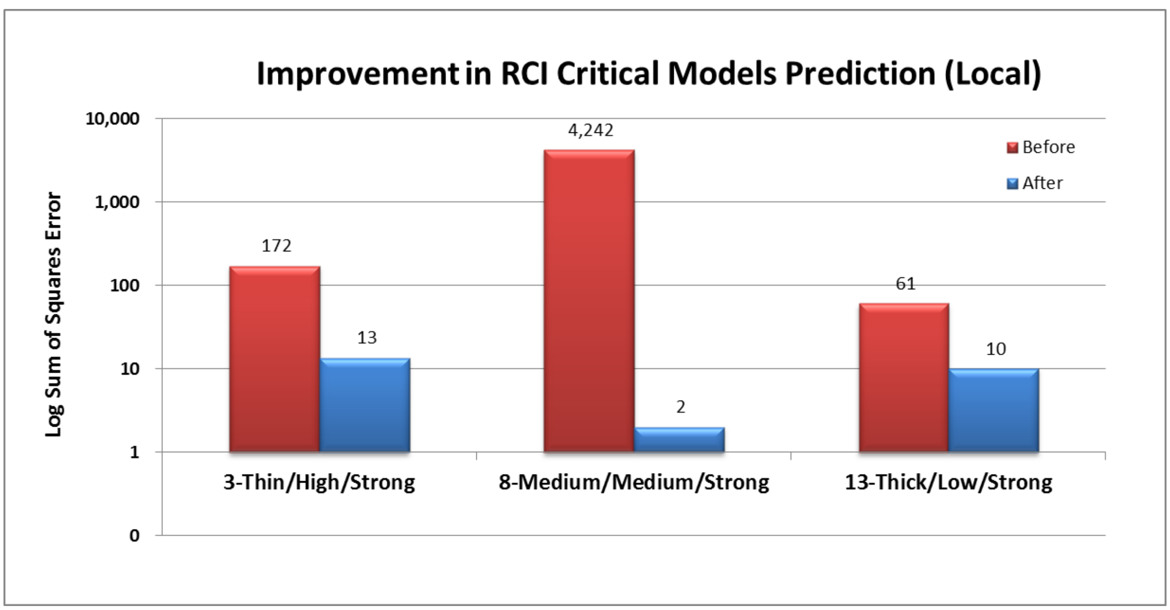


Figure 3-19: Improvement in RCI Model Prediction (Local Road)

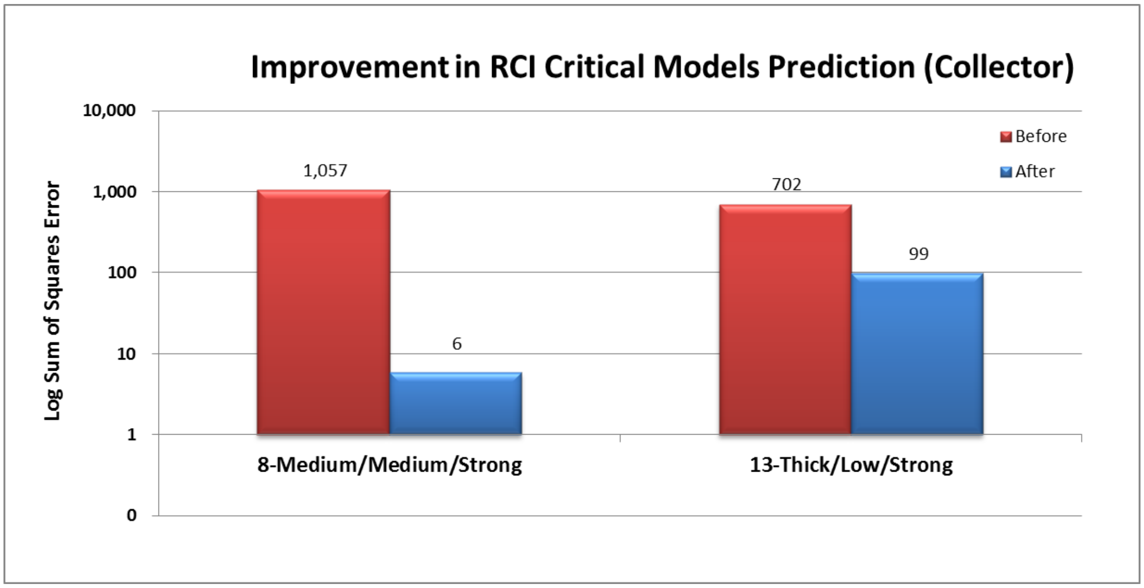


Figure 3-20: Improvement in RCI Model Prediction (Collector Road)

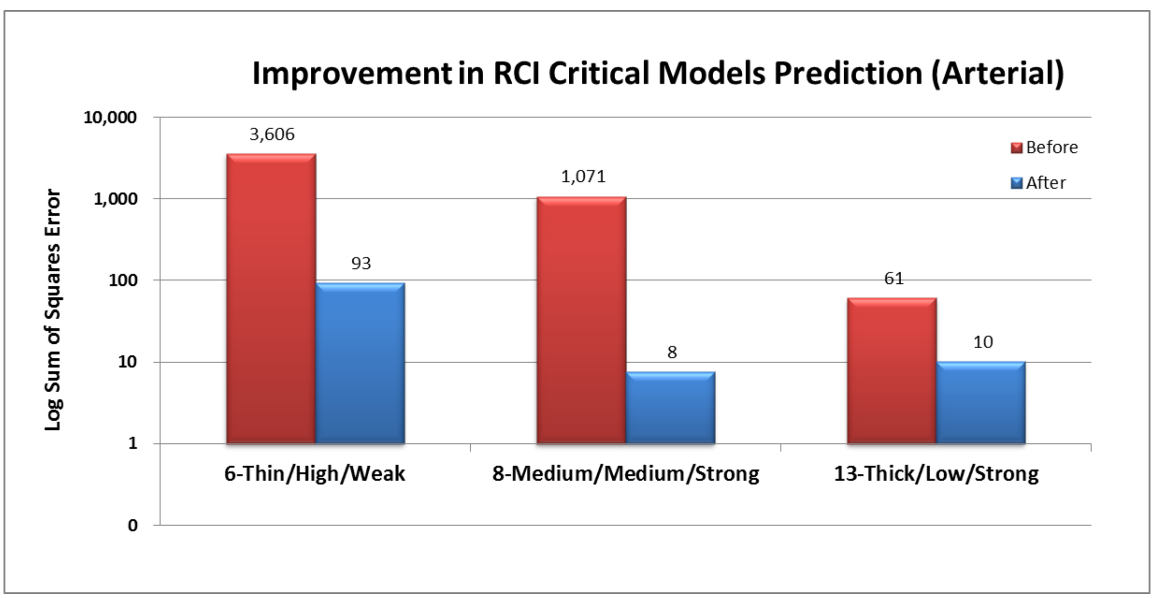


Figure 3-21: Improvement in RCI Model Prediction (Arterial Road)

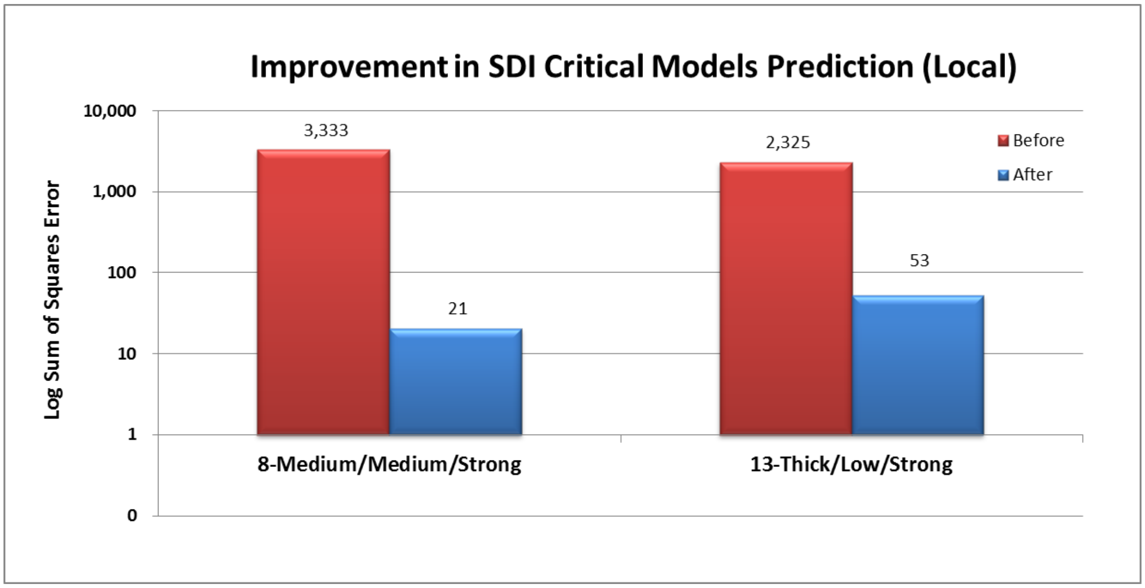


Figure 3-22: Improvement in SDI Model Prediction (Local Road)

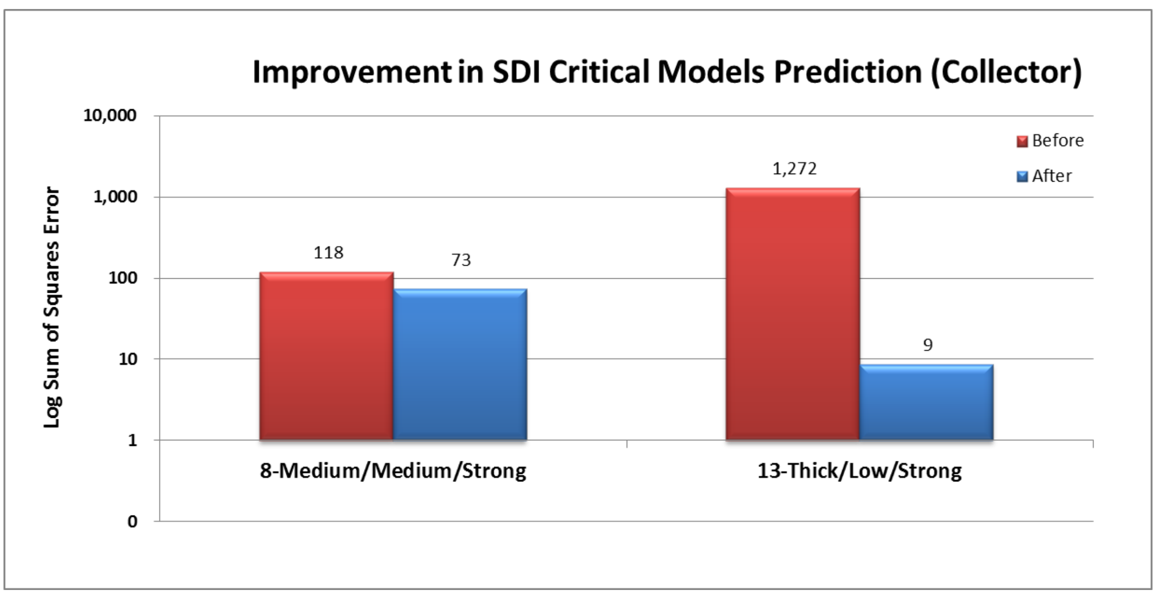


Figure 3-23: Improvement in SDI Model Prediction (Collector Road)

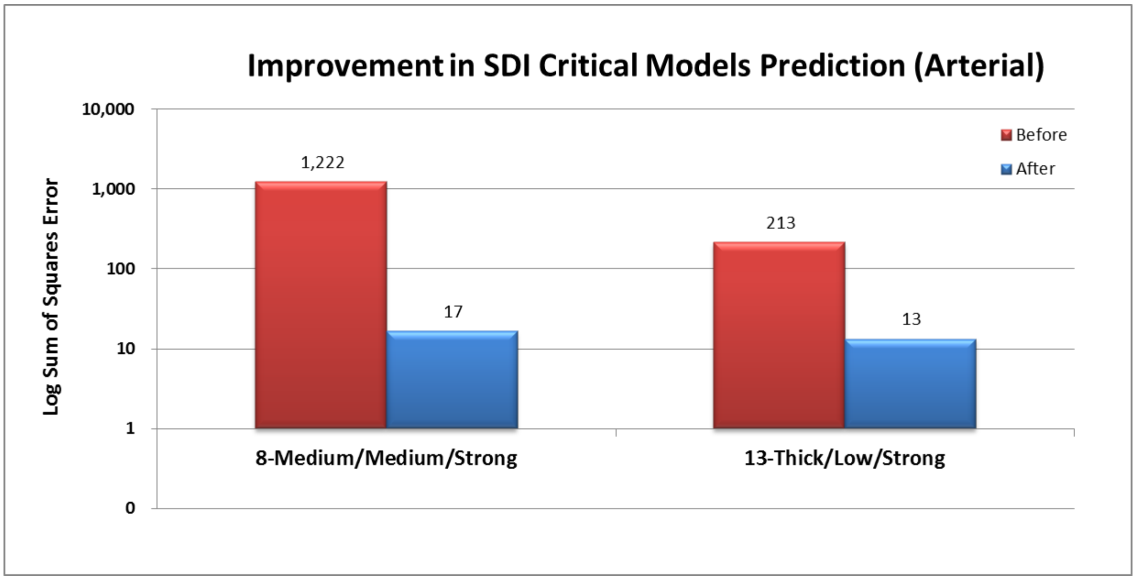


Figure 3-24: Improvement in SDI Model Prediction (Arterial Road)

3.10 SUMMARY

The analysis presented in this section provides a promising approach to improving prediction model development when faced with limited historical data for municipal PMS. Its findings can be summarized as follows:

- Through data aggregation and filtering of PMS data, observations were grouped into 18 performance classes
- Performance classes represent various levels of pavement thickness, traffic load, and subgrade condition
- Based on engineering judgment and local experience, expected ranges of service were developed for each performance class
- A sigmoidal model was used due to its flexibility in terms of describing the deterioration of pavement performance

- Initial sigmoidal model coefficients were developed based on engineering judgment and local experience
- Model coefficients were developed for each section in the database, and the least squares error was calculated and summed for each section
- A linear programming optimization technique was employed to minimize the error for each section
- The optimization included a constraint to limit the service life to the pre-defined expected service lives for each performance class
- The various coefficients were evaluated to determine the most representative coefficients for each performance class

The next Chapter discusses the impact of climate change on pavement performance and will develop preliminary empirical models for Western Canada region and compare it to the one developed in this section.

4.0 Climatic Impact on Empirical Performance Models

4.1 INTRODUCTION

The natural environment is one of the main factors affecting the design and performance of roads and other transportation infrastructure. All types of infrastructure, including pavement structures, are vulnerable to weather events and climate change, which necessitates good planning at all governmental levels. It is always more economical and efficient to design structures to accommodate dominant climate conditions before they are built than to conduct retrofits and repairs at later stages of the service life of the structure. Major climate changes are inherent to both the East and West Coast regions in Canada due to their close proximity to the Atlantic and Pacific oceans. More than 80 percent of Canada's coastline is in the process of submerging due to rising sea levels. Areas where the sea level is stable are also at risk because of the significant change in storm frequency. Of greatest concern are highly developed areas, such as the lower mainland of British Columbia, that have already experienced extensive infrastructure damage (N. R. Canada 2007). Although this phenomenon is nationwide, it affects distinct regions in different ways: while the West Coast is more prone to changes in both the frequency and pattern of storms, the East Coast is more prone to rising sea levels, storm surges, accelerated coastal erosion and hurricanes (E. Canada 2011).

Different types of roads (including highways, and arterial, collector and local roads) have different types of surface types and road base designs to accommodate for their particular intended use. Considering the impact of climate change on road performance, the distinction between the types of roads affects how municipalities and government transportation agencies will adapt. For instance, severe winters may lead to safety concerns, as icy roads become more prevalent. On the other hand, early break-up in spring may reduce the duration of spring load restrictions season, which may lead to an increase in number of trucks travelling on the roads during the shortened winter season.

Climate change also affects the number of freeze-thaw cycles with long periods of freezing increasing during winter seasons in Canada. The increase in wild conditions and freeze-thaw cycles in winter allows snow and/or water to dissipate into already cracked pavement. Water expands and contracts as it freezes and melts during the freeze-thaw cycles, producing changes in volume that may lead to crack enlargement and potholes as the cycles are repeated. It is expected that the rate of deterioration between pavement structures will vary due to climatic variation between the eastern and western regions of Canada. The following section reports on the development of an empirical deterioration model for flexible pavement in Western Canada, comparing it to the one developed previously for Ontario.

4.2 DATA AGGREGATION FOR WESTERN CANADA REGION

The data used in this section was extracted from the pavement management system used for the Cities of Burnaby and Nanaimo in British Columbia. This pavement management database contained historical data collected over a span of 18 years. Not all sections were surveyed during each data collection survey, and surveys were not collected on an annual basis. As mentioned before, it is usually recommended that condition surveys for pavement roughness and distress be collected every three years. This would allow transportation agencies to monitor specific conditions in their local pavement structures, maximizing the efficiency of such structures. Table 4-1 shows the centerline lane lengths for sections used in the analysis for each city. These lengths are for flexible pavement types only. Table 4-2 shows the total number of sections that have been extracted from the different systems with observations. The table also indicates how many sections have records for each performance index, as well as, the number of observations per section.

Table 4-1: Sections Lengths

City	Length (KM)
Nanaimo	419
Burnaby	725
Grand Total	**1,144**

Table 4-2: Number of Sections with Observations by PI for Western Region

PI	No. Sections with Observations	No. of Observations per Section			
		1	2	3	4
RCI	2,155		1,459	654	2
SDI	2,402		1,729	672	1

Similar to the steps followed in Chapter 3's development of the empirical performance model for Ontario, several steps were executed to filter the data and remove outliers and unrealistic records. Sections that had only one observation were removed, while sections with two or more observations were further investigated and filtered out if the span between consecutive observations was too long to ensure that no rehabilitation activity had been performed in this period. In addition, with the absence of any construction records, sections that did not have a deteriorating trend were removed from the data set used in developing the model, as sections were expected to deteriorate over time, and it was assumed that any performance enhancement was the result of a rehabilitation-type activity. Models were developed only for sections where enough reliable data was available to produce deterioration models.

4.3 DEVELOPMENT OF ENHANCED EMPIRICAL MODELS FOR WESTERN CANADA

Table 4-3 and Table 4-4 show the final model coefficients for categories in which historical data was sufficiently available to produce models for Western Canada. This analysis was carried out using the same principles previously used for the Eastern Canada region, as demonstrated in Chapter 3. An optimization technique was employed to minimize the square mean error between the actual measurements and the model predictions, while maintaining the pavement service life within the ranges expected for each category. This analysis resulted in 18 model coefficients for each functional class. Categories in which not enough data was available to produce the models were designated with NA. it should be noted that data

Table 4-3: RCI Models Coefficients for Different Functional Classes (Western Region)

Model ID	Thickness	Traffic	Subgrade	RCI Model Coefficients											
				Local				Collector				Arterial			
				a	b	c	Age	a	b	c	Age	a	b	c	Age
1	Thin	Low	Strong	4.25	3.84	2.13	25.2	4.42	6.44	2.14	22.0	4.52	7.75	2.12	19.5
2	Thin	Med.	Strong	4.32	4.25	2.13	22.1	4.06	2.61	2.13	21.3	NA	NA	NA	NA
3	Thin	High	Strong	4.39	4.50	2.13	19.4	4.46	5.76	2.17	16.6	4.02	2.58	2.18	14.0
4	Thin	Low	Weak	4.79	8.07	2.16	17.8	4.20	3.16	2.14	15.5	NA	NA	NA	NA
5	Thin	Med.	Weak	4.37	3.78	2.16	15.7	4.25	3.70	2.20	14.9	NA	NA	NA	NA
6	Thin	High	Weak	4.45	3.92	2.13	13.6	4.30	3.34	2.18	11.7	NA	NA	NA	NA
7	Med.	Low	Strong	4.14	2.87	2.11	29.8	4.09	3.49	2.11	28.2	NA	NA	NA	NA
8	Med.	Med.	Strong	4.26	4.09	2.13	26.1	4.19	3.91	2.14	21.6	4.25	4.72	2.13	16.7
9	Med.	High	Strong	4.43	5.53	2.14	22.5	4.53	6.97	2.16	19.1	4.38	6.05	2.16	16.8
10	Med.	Low	Weak	4.64	7.59	2.18	20.1	4.03	2.07	2.10	20.1	4.15	3.73	2.13	15.7
11	Med.	Med.	Weak	4.42	4.82	2.17	18.1	4.82	8.12	2.20	14.0	NA	NA	NA	NA
12	Med.	High	Weak	4.51	4.92	2.14	15.9	4.50	5.05	2.15	13.5	NA	NA	NA	NA
13	Thick	Low	Strong	4.35	6.67	2.17	34.3	3.89	1.00	2.10	26.5	3.81	1.38	2.10	25.5
14	Thick	Med.	Strong	4.18	3.44	2.10	31.2	4.95	12.61	2.12	24.2	4.26	5.75	2.14	20.9
15	Thick	High	Strong	4.56	7.47	2.14	24.9	4.51	7.54	2.17	21.4	4.29	5.45	2.14	18.2
16	Thick	Low	Weak	5.15	15.00	2.20	23.6	4.75	9.43	2.14	20.8	3.80	0.95	2.10	18.5
17	Thick	Med.	Weak	5.53	14.98	2.10	20.1	NA	NA	NA	NA	4.18	3.85	2.13	15.3
18	Thick	High	Weak	4.61	6.10	2.13	17.5	4.65	7.21	2.16	16.1	4.00	2.20	2.11	13.5

Note: NA refers to models where no enough data was available to produce models

Table 4-4: SDI Models Coefficients for Different Functional classes (Western Region)

Model ID	Thickness	Traffic	Subgrade	SDI Model Coefficients											
				Local				Collector				Arterial			
				a	**b**	**c**	**Age**	**a**	**b**	**c**	**Age**	**a**	**b**	**c**	**Age**
1	Thin	Low	Strong	5.99	7.87	1.48	29.3	5.99	7.78	1.49	24.4	5.96	7.57	1.5	19.6
2	Thin	Med.	Strong	5.99	7.45	1.48	25.5	6.00	7.57	1.5	21.3	NA	NA	NA	NA
3	Thin	High	Strong	5.99	6.99	1.48	21.7	5.99	6.88	1.49	18.1	5.98	6.70	1.49	14.4
4	Thin	Low	Weak	5.99	6.94	1.49	20.5	6.00	6.66	1.48	17.1	NA	NA	NA	NA
5	Thin	Med.	Weak	5.99	6.45	1.48	17.9	NA	NA	NA	NA	NA	NA	NA	NA
6	Thin	High	Weak	5.99	6.09	1.48	15.2	6.00	5.89	1.48	12.6	NA	NA	NA	NA
7	Med.	Low	Strong	5.99	8.30	1.48	34.5	5.99	8.24	1.48	28.8	NA	NA	NA	NA
8	Med.	Med.	Strong	5.99	8.00	1.49	30.0	5.99	7.89	1.49	25.0	6.00	7.56	1.49	20.0
9	Med.	High	Strong	5.99	7.50	1.49	25.5	6.00	7.28	1.48	21.3	5.99	7.01	1.48	17.0
10	Med.	Low	Weak	5.98	7.38	1.49	24.2	6.00	7.29	1.49	20.1	6.00	7.12	1.5	16.1
11	Med.	Med.	Weak	6.00	6.93	1.48	21.0	5.98	6.94	1.5	17.5	5.94	6.56	1.5	14.0
12	Med.	High	Weak	5.99	6.45	1.48	17.9	6.00	6.34	1.48	14.9	NA	NA	NA	NA
13	Thick	Low	Strong	5.99	9.07	1.49	39.7	5.98	8.98	1.5	33.1	6.00	8.35	1.48	26.5
14	Thick	Med.	Strong	6.00	8.43	1.48	34.5	6.00	7.83	1.46	28.8	5.99	7.75	1.47	23.0
15	Thick	High	Strong	6.00	7.95	1.49	29.3	6.00	7.71	1.48	24.4	5.99	7.50	1.49	19.6
16	Thick	Low	Weak	6.00	8.04	1.5	27.8	6.00	7.84	1.5	23.1	6.00	7.55	1.5	18.5
17	Thick	Med.	Weak	6.00	7.59	1.5	24.2	5.96	6.71	1.46	20.1	NA	NA	NA	NA
18	Thick	High	Weak	6.00	7.11	1.5	20.5	5.98	6.69	1.49	17.1	5.99	6.47	1.49	13.7

Note: NA refers to models where no enough data was available to produce models

Figure 4-1 to Figure 4-6 show the average predicted service life and expected service life range for critical models for the Western Canada region. The graphs also show initial error in model prediction before optimization, as calculated from equation 3.2, as well as the final error after the optimization procedure. The graphs show that all critical models met the expected service life within acceptable error tolerance.

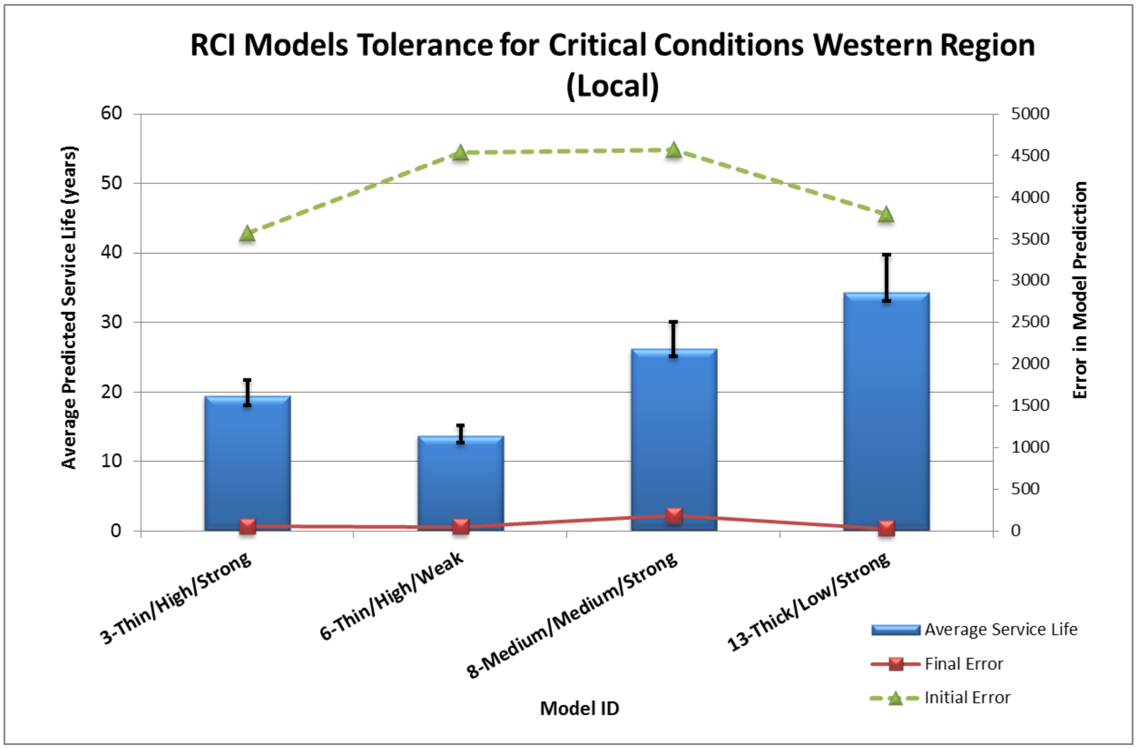


Figure 4-1: RCI Models Tolerance for Critical Models Western Region (Local Roads)

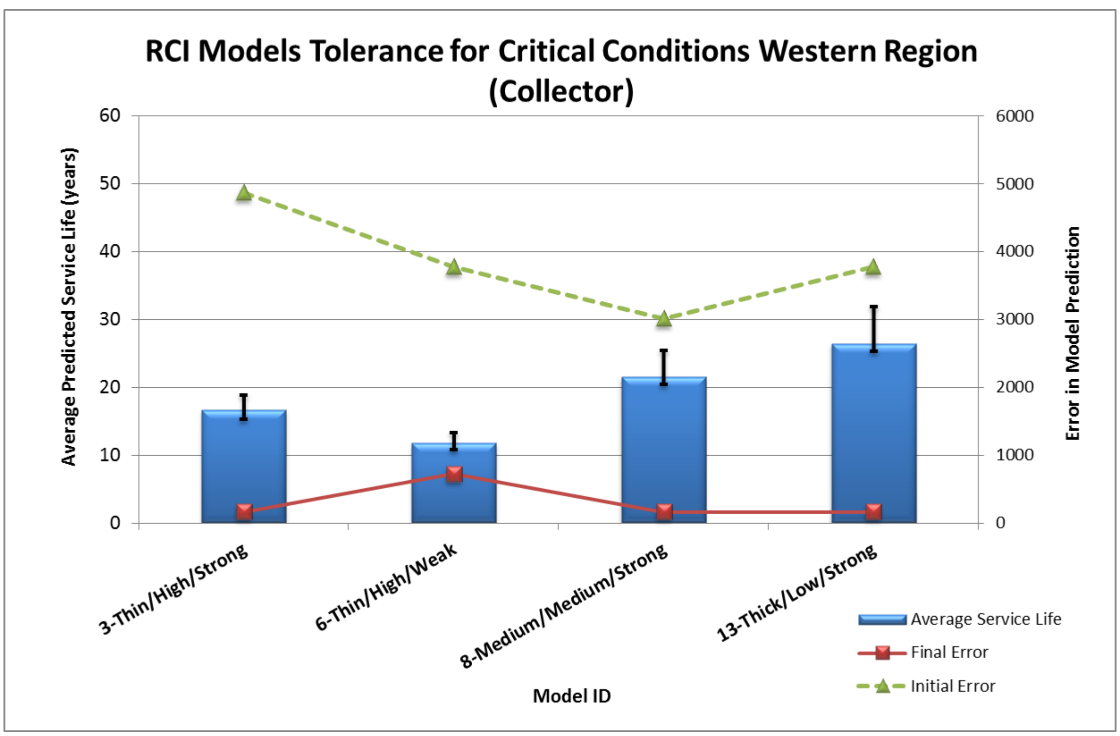


Figure 4-2: RCI Models Tolerance for Critical Models Western Region (Collector Roads)

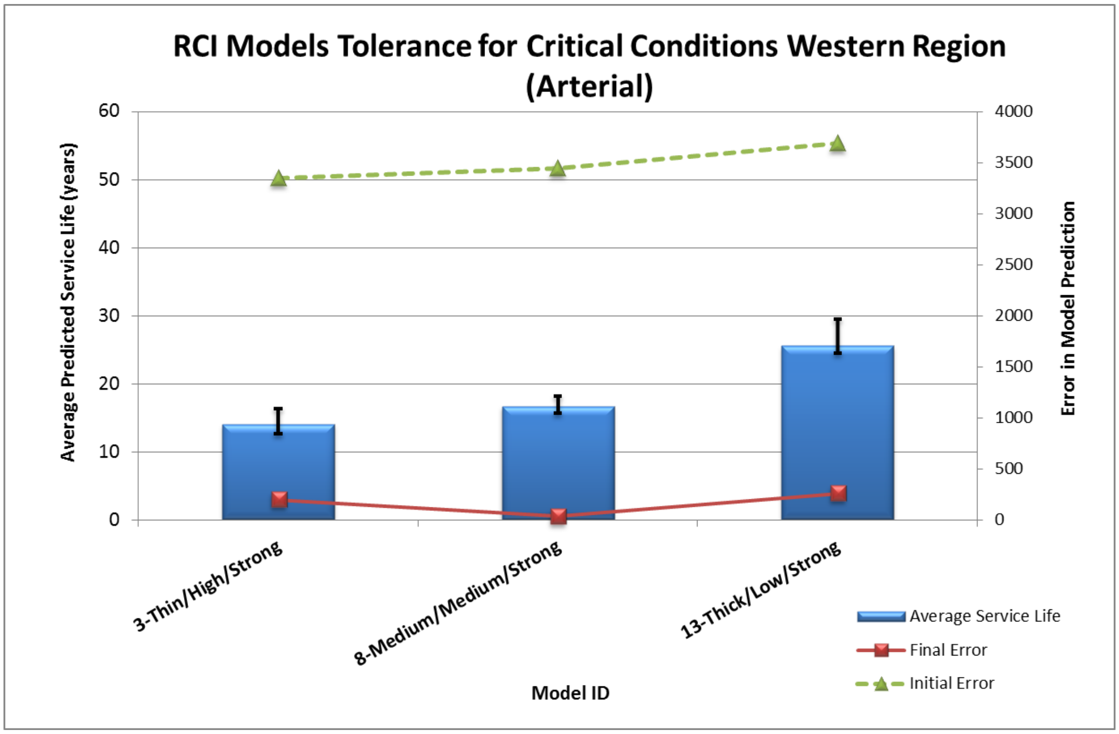


Figure 4-3: RCI Models Tolerance for Critical Models Western Region (Arterial Roads)

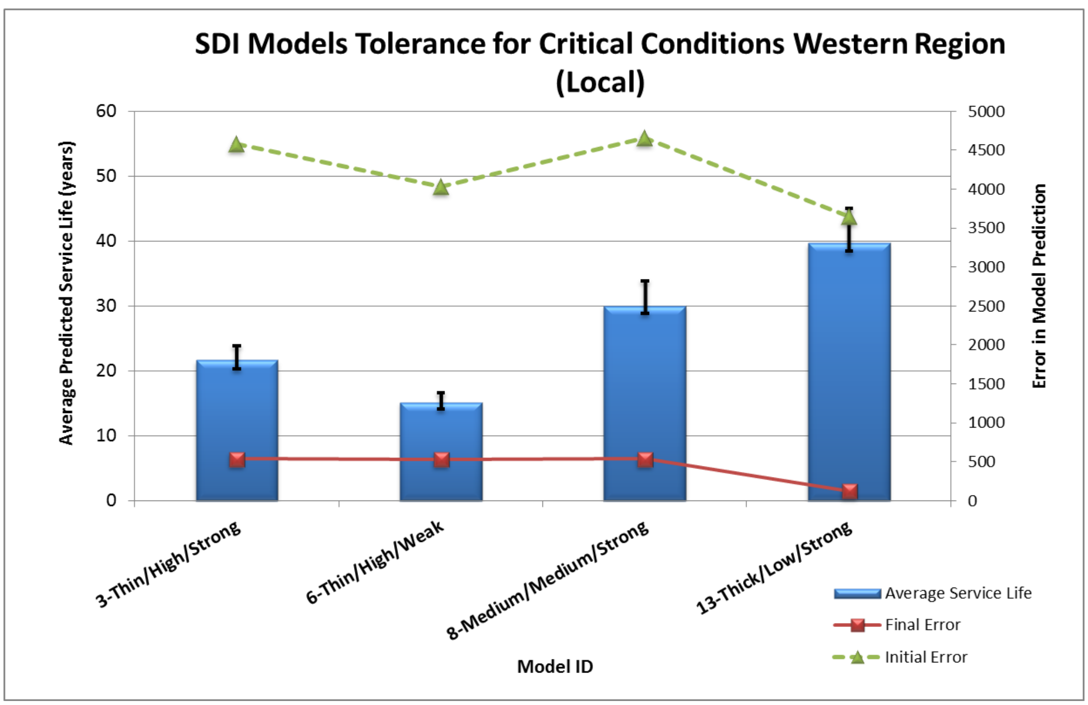


Figure 4-4: SDI Models Tolerance for Critical Models Western Region (Local Roads)

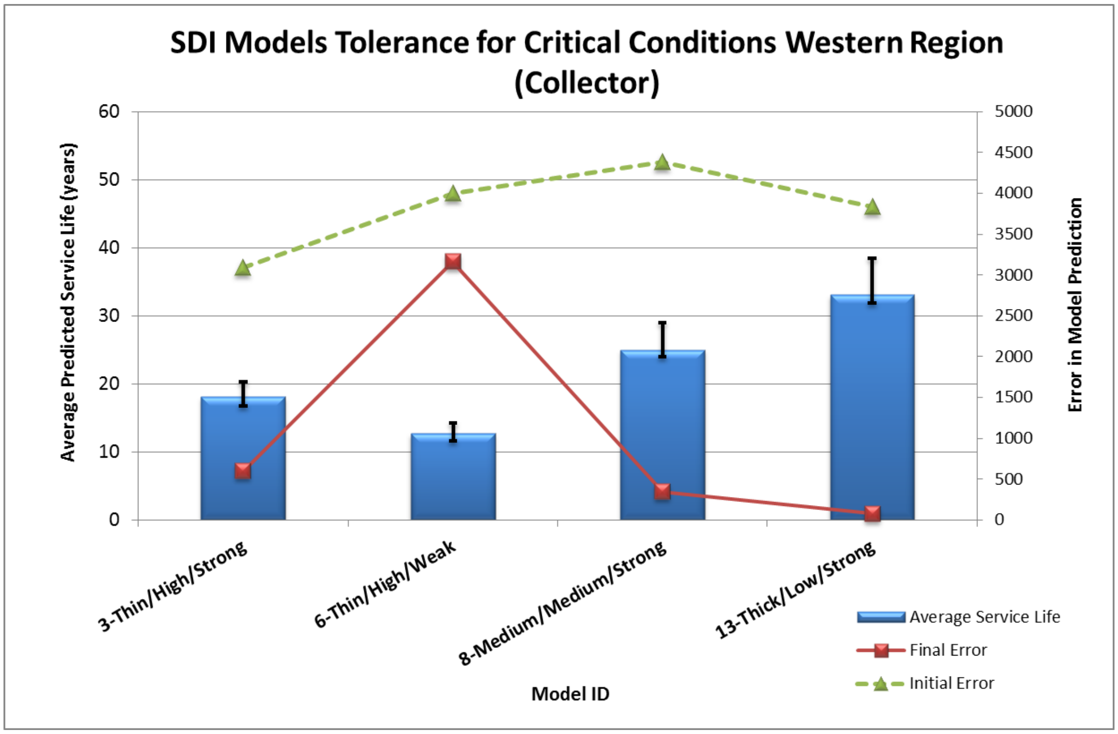


Figure 4-5: SDI Models Tolerance for Critical Models Western Region (Collector Roads)

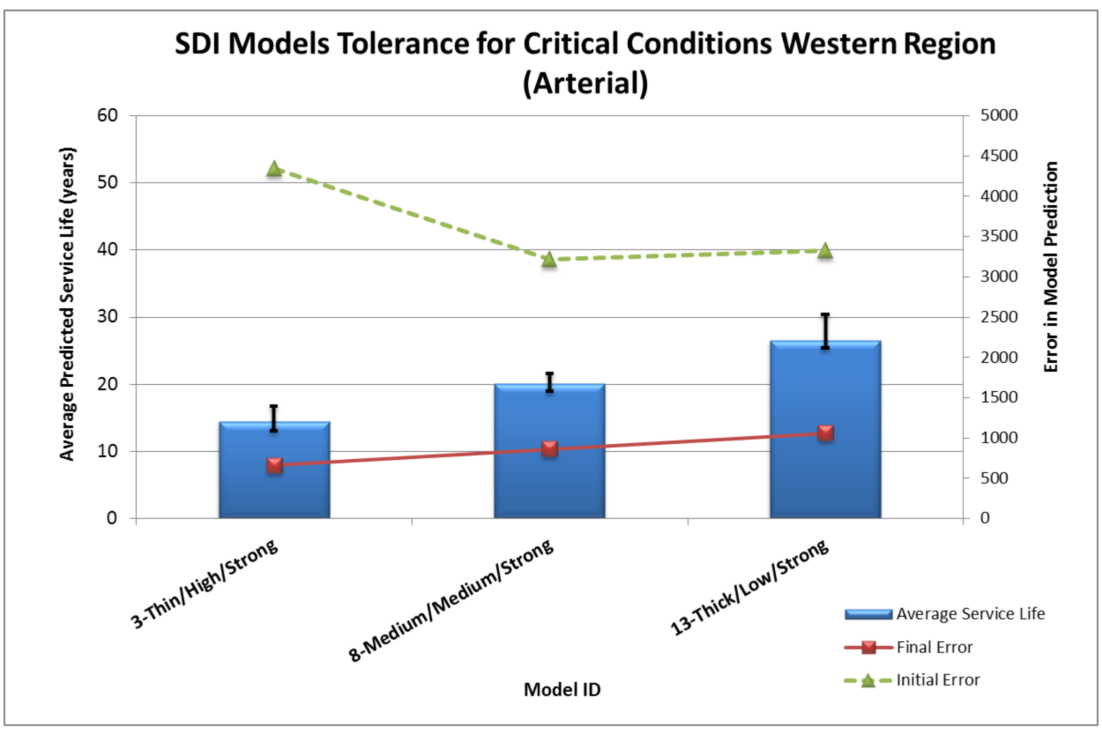


Figure 4-6: SDI Models Tolerance for Critical Models Western Region (Arterial Roads)

4.4 COMPARISON BETWEEN EASTERN AND WESTERN EMPIRICAL MODELS

Figure 4-7 to Figure 4-9 show the comparison between the RCI models developed for Western Canada compared to those developed for Eastern Canada (Ontario), with only the main extreme categories shown. It can be seen that the RCI predicted measurements for all functional classes indicate that pavement in the western region tends to deteriorate relatively faster than that in the eastern region during the first few years of its service life. The RCI pavement condition then stabilized during the remainder of the pavement's service life. Although technology has become more readily available for measuring road roughness in recent decades, it has still not fully matured. A prevailing sense exists in the road community that if every agency measured the same road with their own device, they would each obtain a different result. Errors in profile and discrepancies between measurements arise from variations in equipment, inappropriate operating procedures, and specific aspects of the pavement surface and surrounding environment. In many cases, these factors interact to reduce their repeatability and accuracy (Brown, Liu and Henning 2010). It has often been believed that variation in initial roughness is due to the quality of initial construction and to the variation in construction practices of different contractor/crews. These practices, along with other influencing factors such as environmental condition and traffic patterns, may have contributed to the greater rate of deterioration in western Canada region as compared to the eastern region.

For the SDI index, the relatively mild weather in Western Canada extended the service life of the flexible pavement in general compared to that in Eastern Canada. As can be seen in Figure 4-10 to Figure 4-12, during the first few years of its life, the Western pavement maintained a relatively good SDI condition for a longer time when compared to that observed in Eastern Canada. This was obviously noticed in arterial and collector sections. After this period of time, the pavement started to deteriorate with a more rapidly declining rate as accumulated distresses started to have a negative impact on pavement condition. During the late winter and early spring seasons, pavement in the eastern region is always subjected to relatively more frequent freeze-thaw cycles that negatively affect the overall SDI pavement condition than in the western region where milder weather conditions prevail during this time of the year. It is important to note that in most cases thick pavement exhibited longer service life than thin pavement. In addition, pavement condition typically does not reach a condition below 20 without preventative maintenance or major rehabilitation activity. Therefore, deterioration models below this limit are rarely used.

Figure 4-13 to Figure 4-18 show a comparison between the resultant service life for the eastern and western regions based on both RCI and SDI modeling. It can be seen that for RCI local and collector roads, the eastern region has consistently longer predicted service life compared to the western region, while arterial sections did not show the same trend for models with data available for comparison (Model 6 and Model 8). The modelling based on SDI showed a reverse trend, with pavement in the western region tending to have a longer service life when compared to pavement in the eastern region. This could be due to the fact that SDI modeling was able to capture the impact of harsh weather in the eastern region, since SDI is mainly aggregated from distresses which are obviously higher in severity in Eastern Canada when compared to the West. The RCI modeling has other parameters that impacted it, such as initial construction and contractor practices, which may hinder clear comparison between the eastern and western regions.

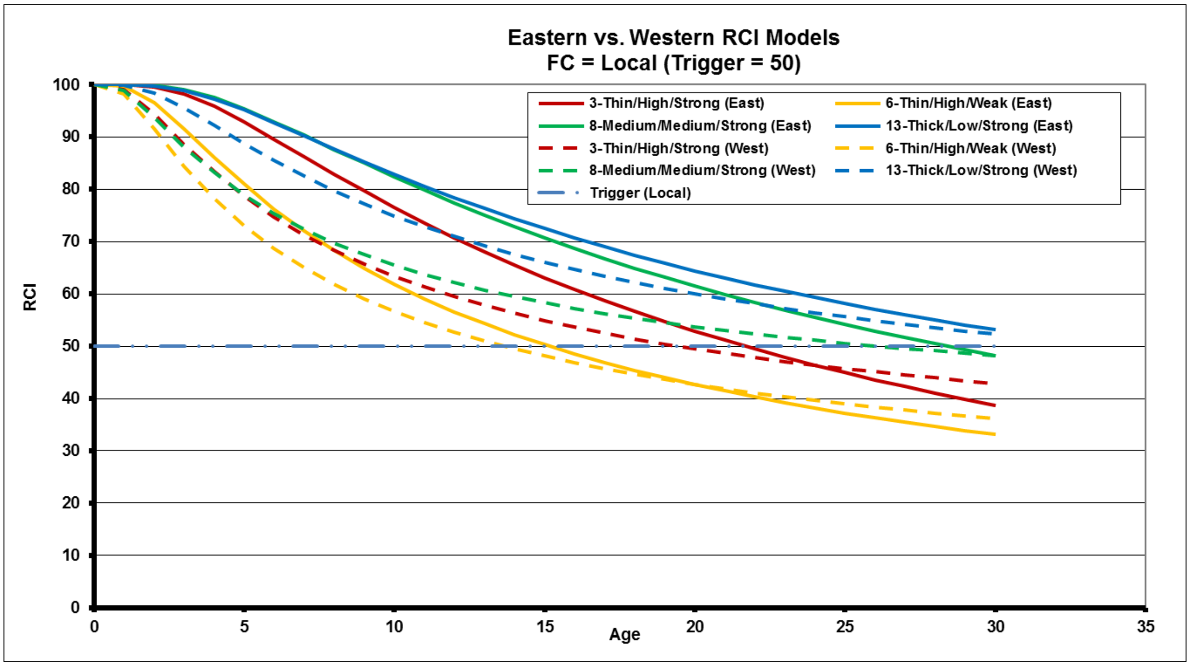


Figure 4-7: Eastern vs. Western Regions Models Comparison (Local Roads)

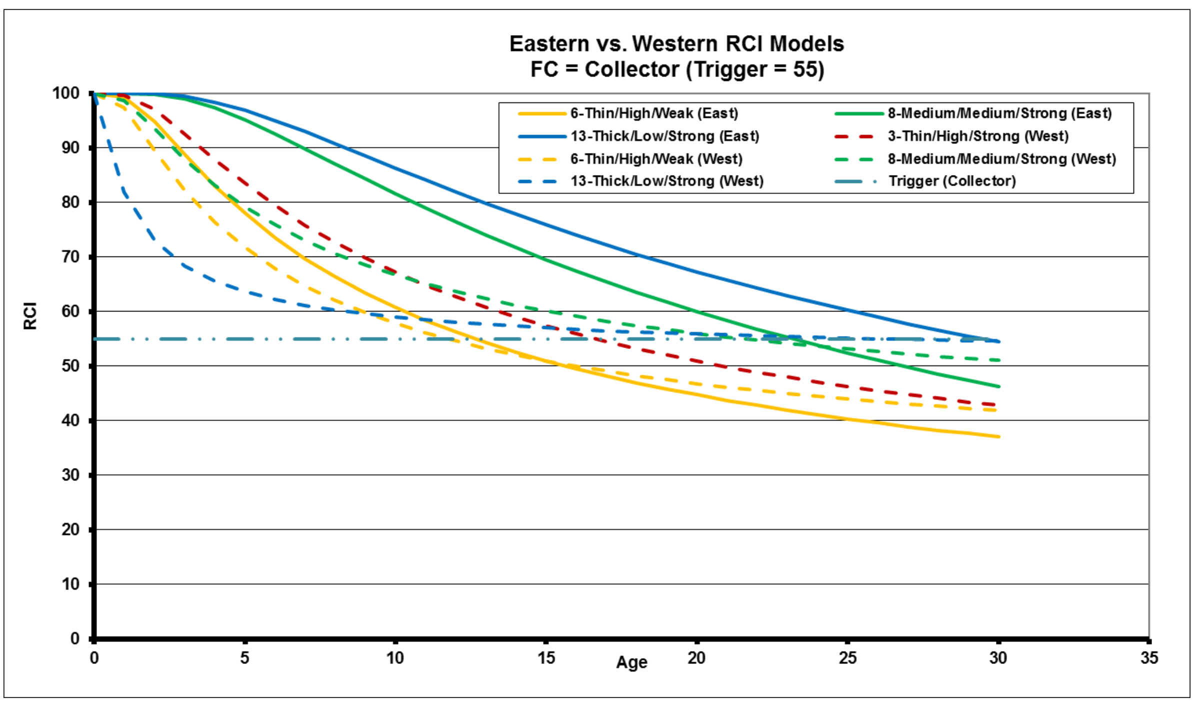


Figure 4-8: Eastern vs. Western Regions Models Comparison (Collector Roads)

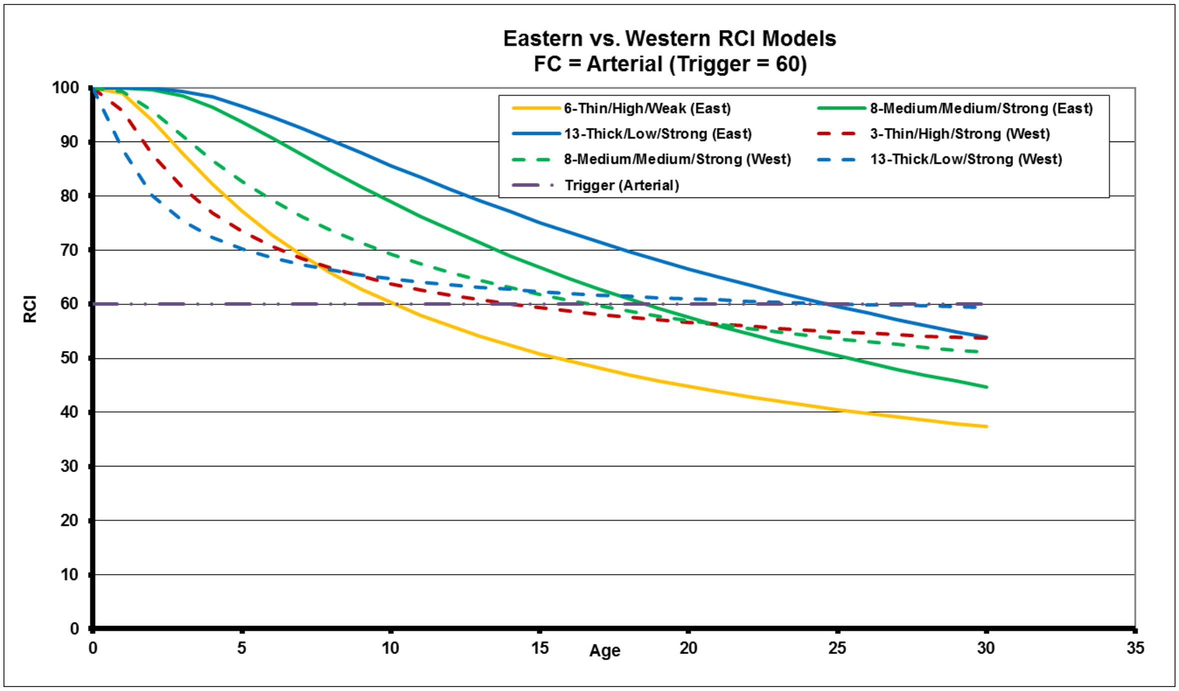


Figure 4-9: Eastern vs. Western Regions Models Comparison (Arterial Roads)

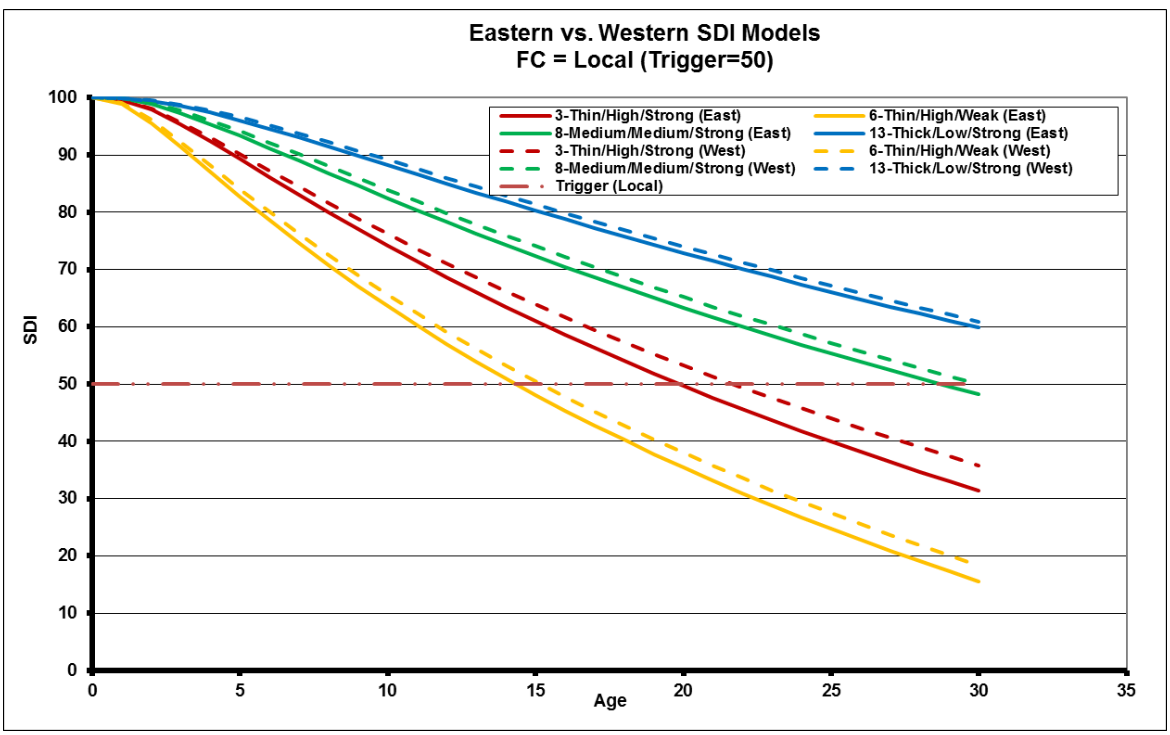


Figure 4-10: Eastern vs. Western Regions Models Comparison (Local Roads)

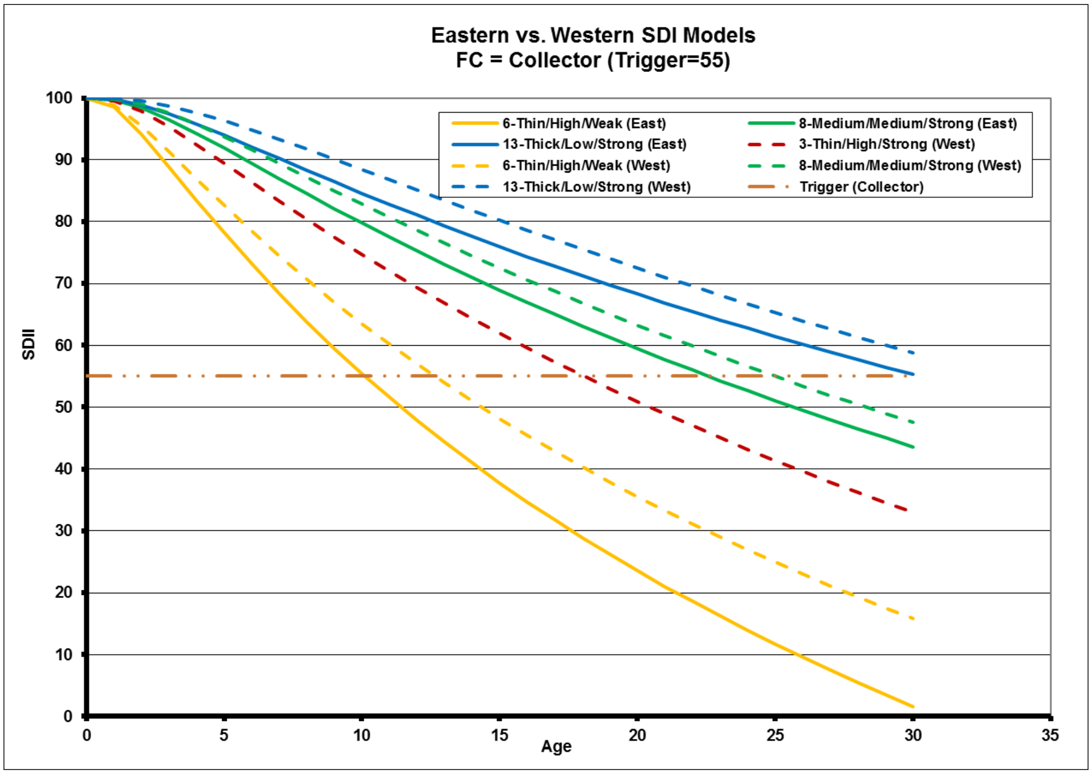


Figure 4-11: Eastern vs. Western Regions Models Comparison (Collector Roads)

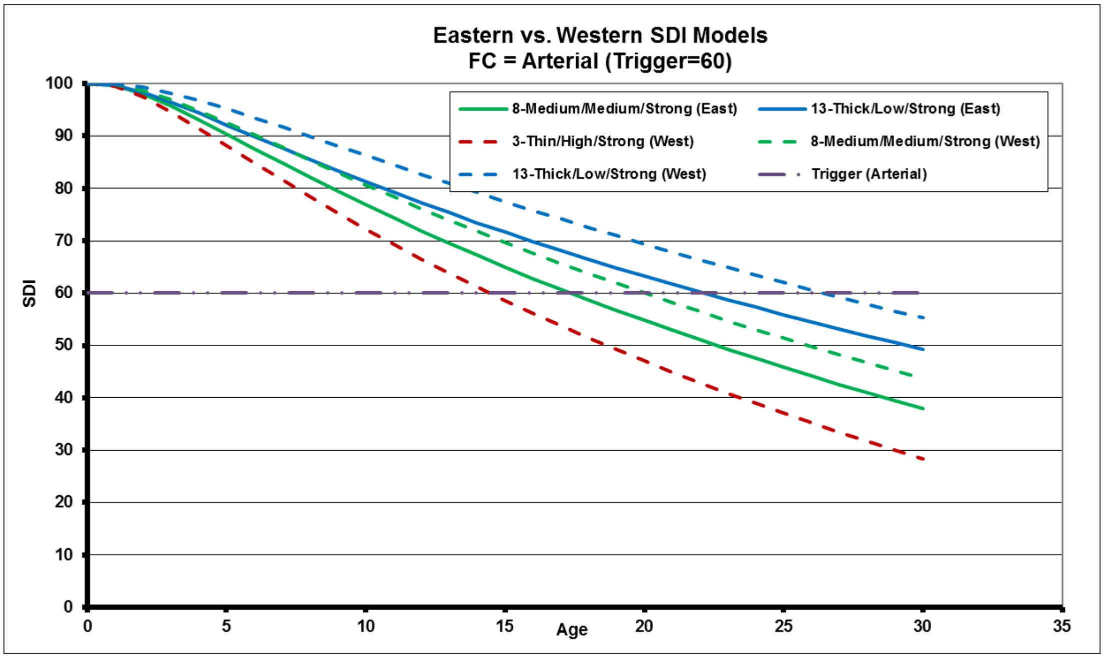


Figure 4-12: Eastern vs. Western Regions Models Comparison (Arterial Roads)

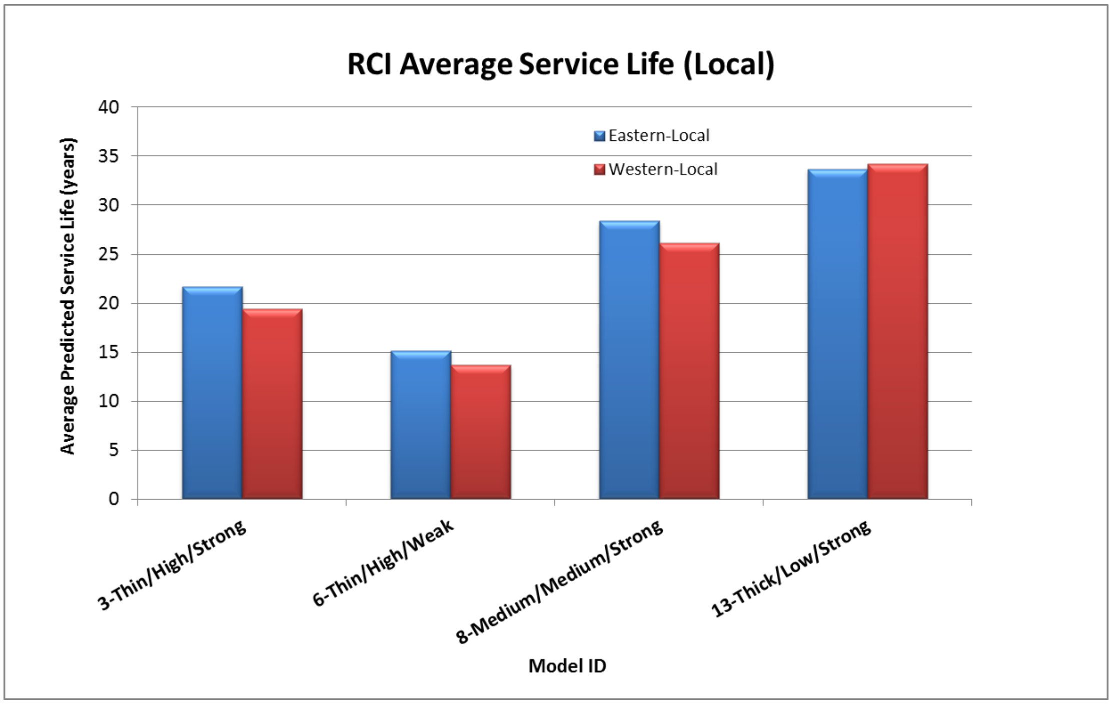


Figure 4-13: Eastern vs. Western Regions Predicted Service Life (RCI - Local Roads)

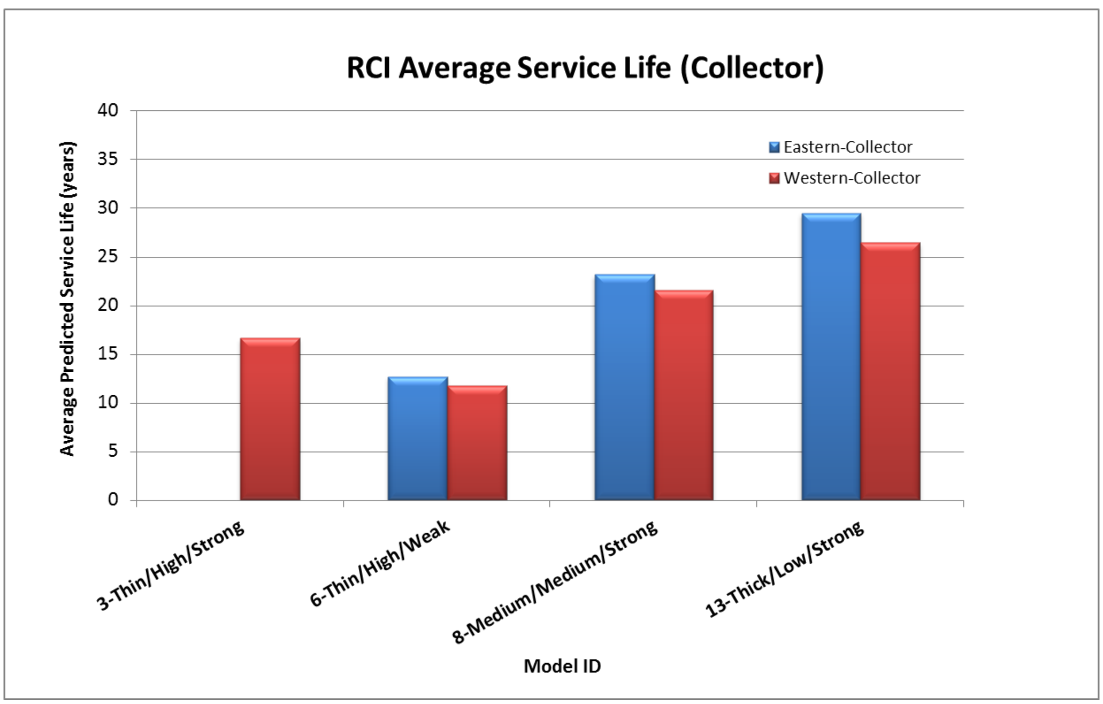


Figure 4-14: Eastern vs. Western Regions Predicted Service Life (RCI - Collector Roads)

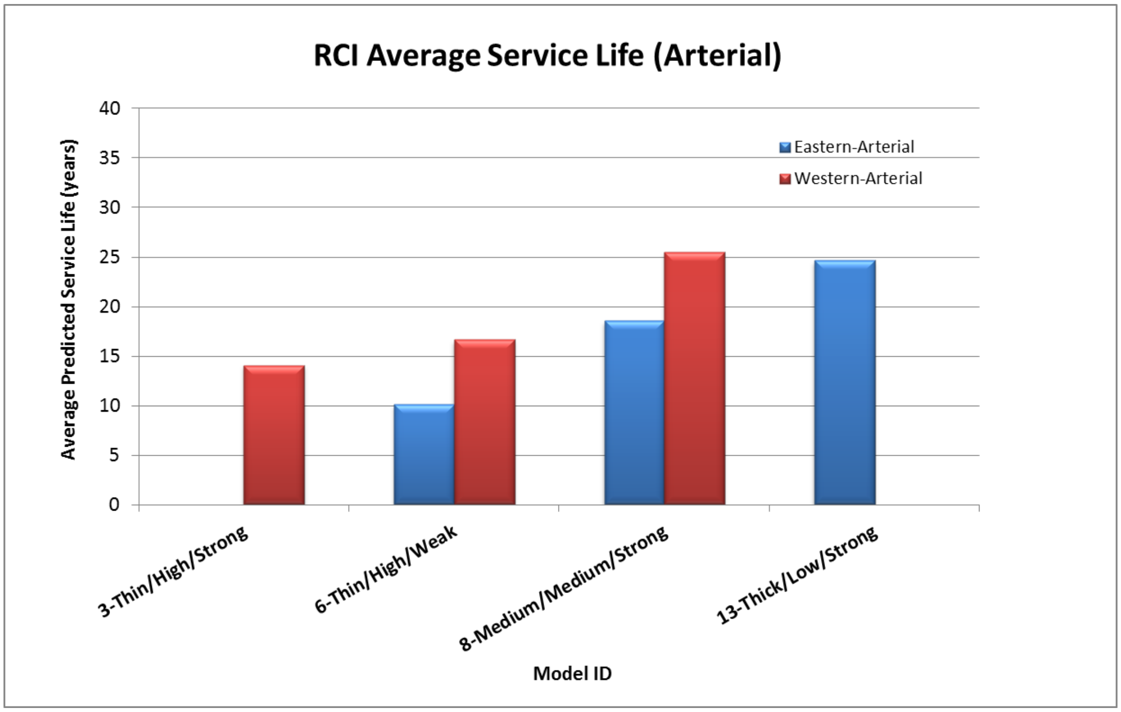


Figure 4-15: Eastern vs. Western Regions Predicted Service Life (RCI - Arterial Roads)

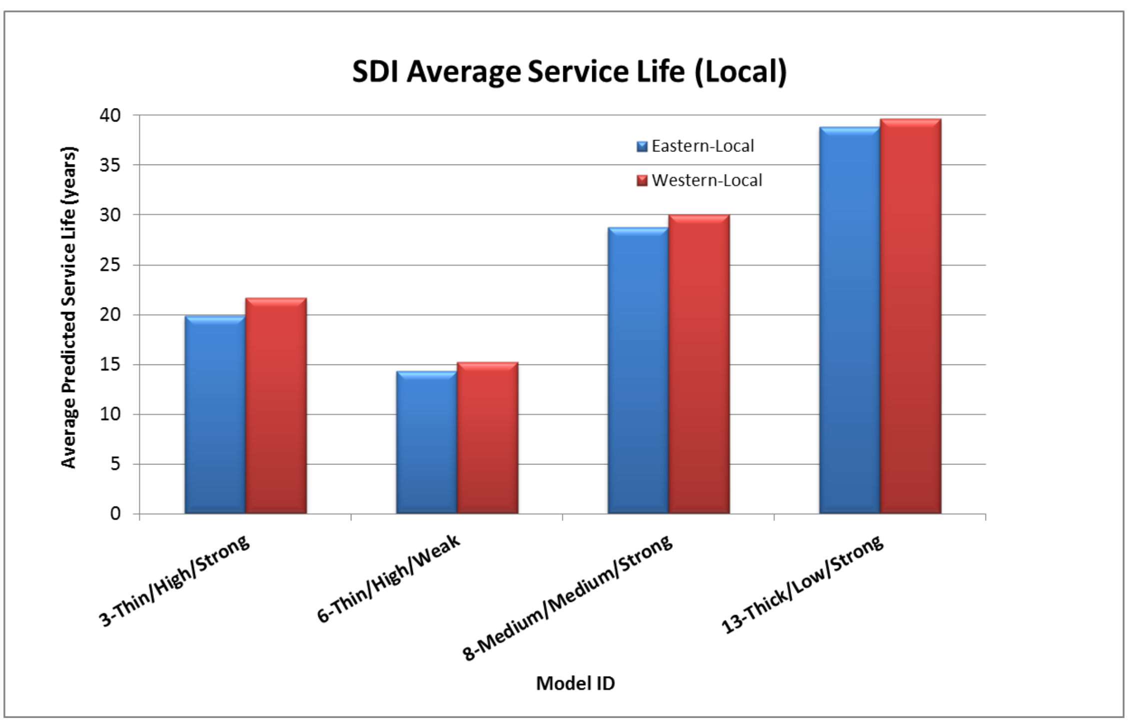


Figure 4-16: Eastern vs. Western Regions Predicted Service Life (SDI - Local Roads)

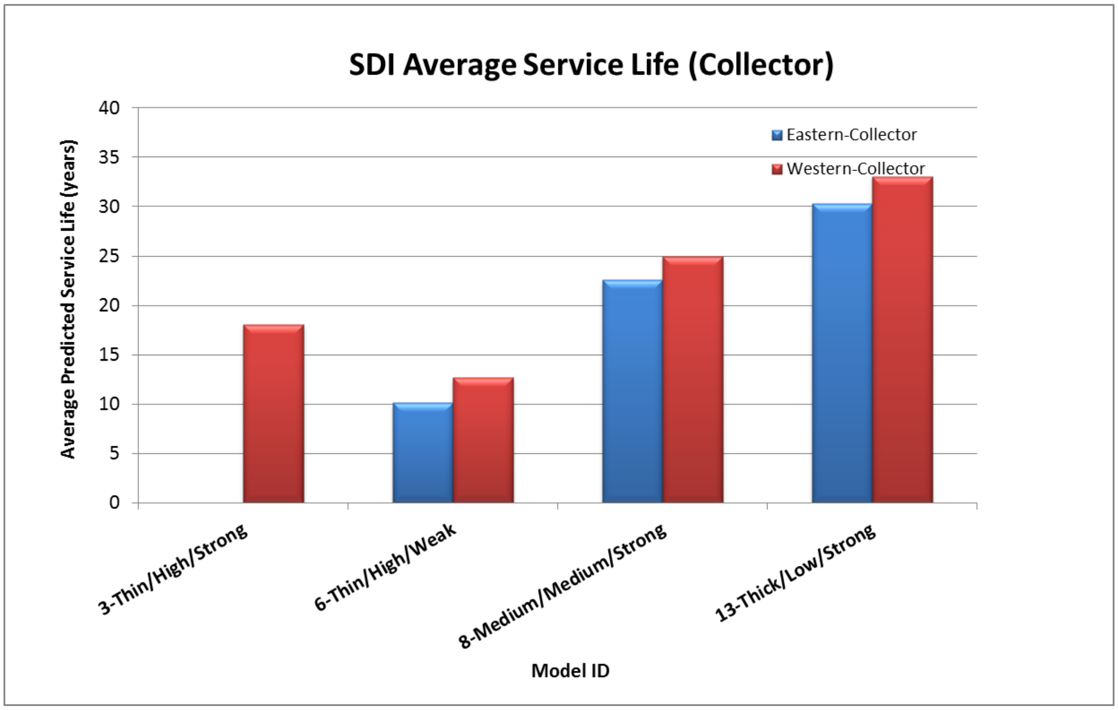


Figure 4-17: Eastern vs. Western Regions Predicted Service Life (SDI - Collector Roads)

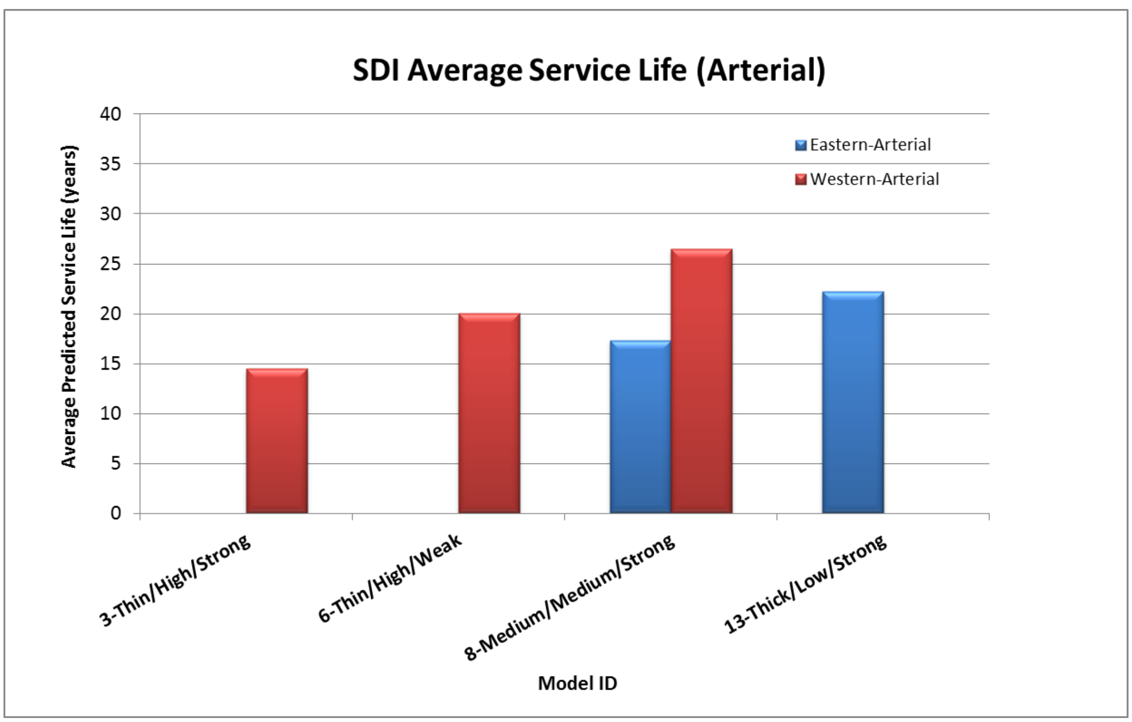


Figure 4-18: Eastern vs. Western Regions Predicted Service Life (SDI - Arterial Roads)

4.5 MODEL VALIDATION

Similar to the model validation process carried out for enhanced empirical model for eastern region, the same process was carried out to validate models developed for western region. Consecutive deteriorating points in excluded sections due to the absence of deterioration trend were used to verify the developed models. One section for each critical condition was identified to verify the developed models. Only critical conditions with sections contain reasonable observations were included in model validation process. Figure 4-19 to Figure 4-24 show the comparison between predicting condition indexes using initial model coefficients before the optimization and after the optimization. Similar to eastern region models, the use of the new developed models showed a significant improvement in the model prediction and reduction in model errors as a result of using the new developed models. The current analysis demonstrates that the developed empirical models for western region have the capability to predict reliable future condition of pavement.

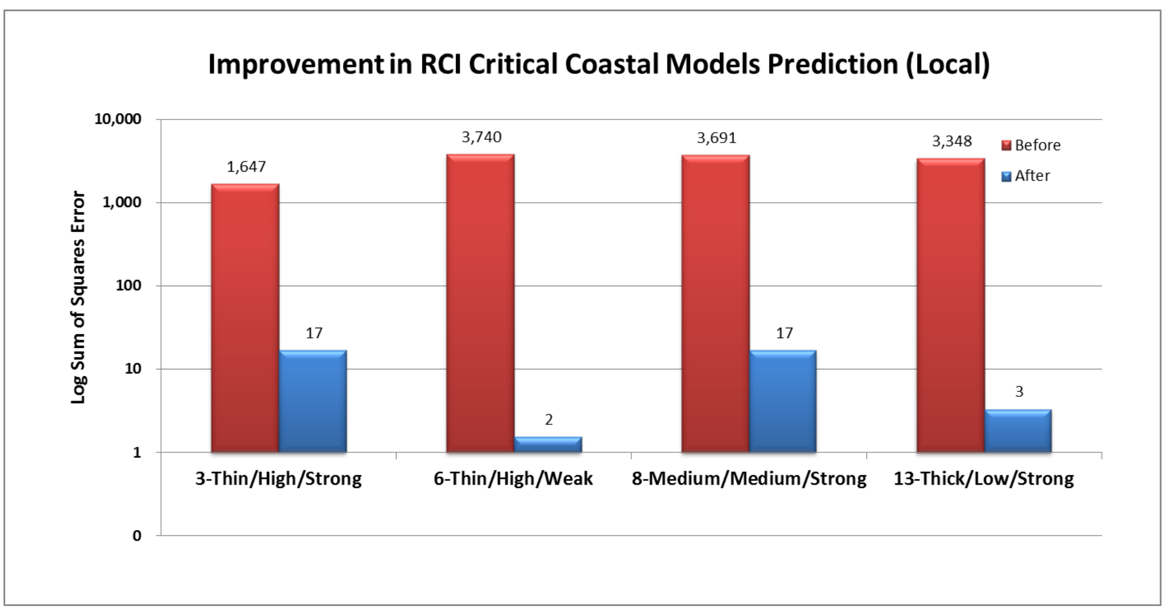


Figure 4-19: Improvement in RCI Model Prediction (Local Road)

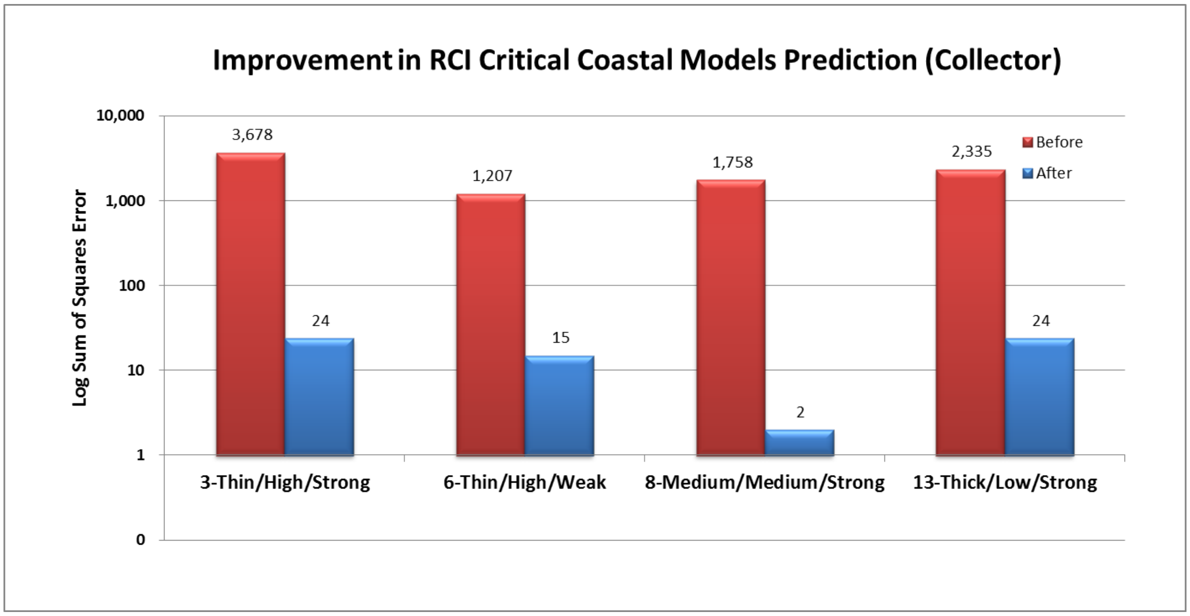


Figure 4-20: Improvement in RCI Model Prediction (Collector Road)

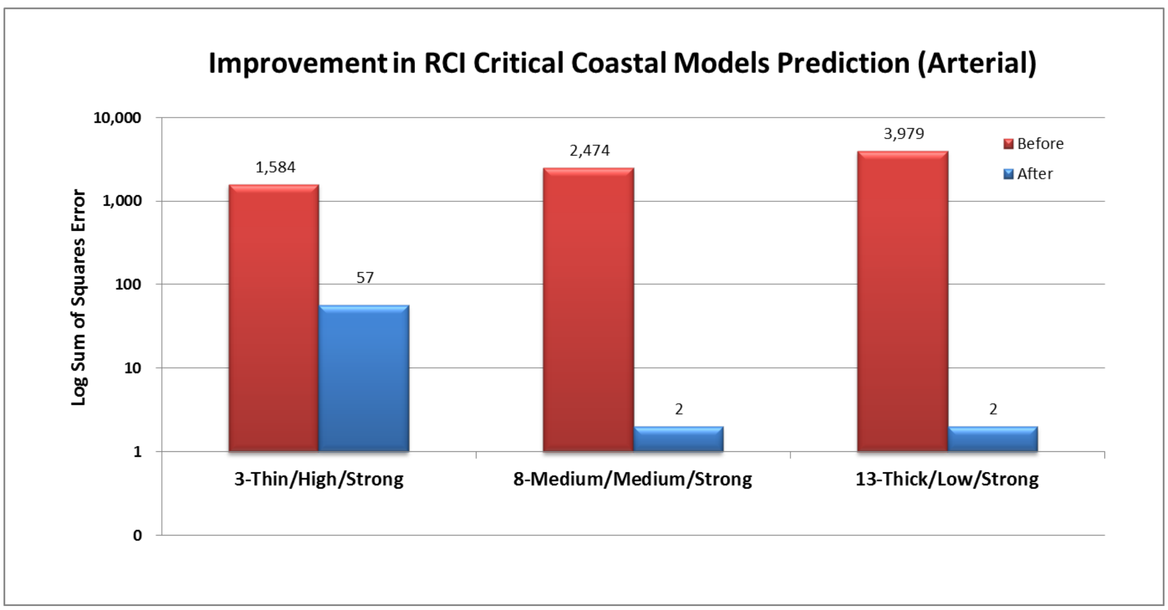


Figure 4-21: Improvement in RCI Model Prediction (Arterial Road)

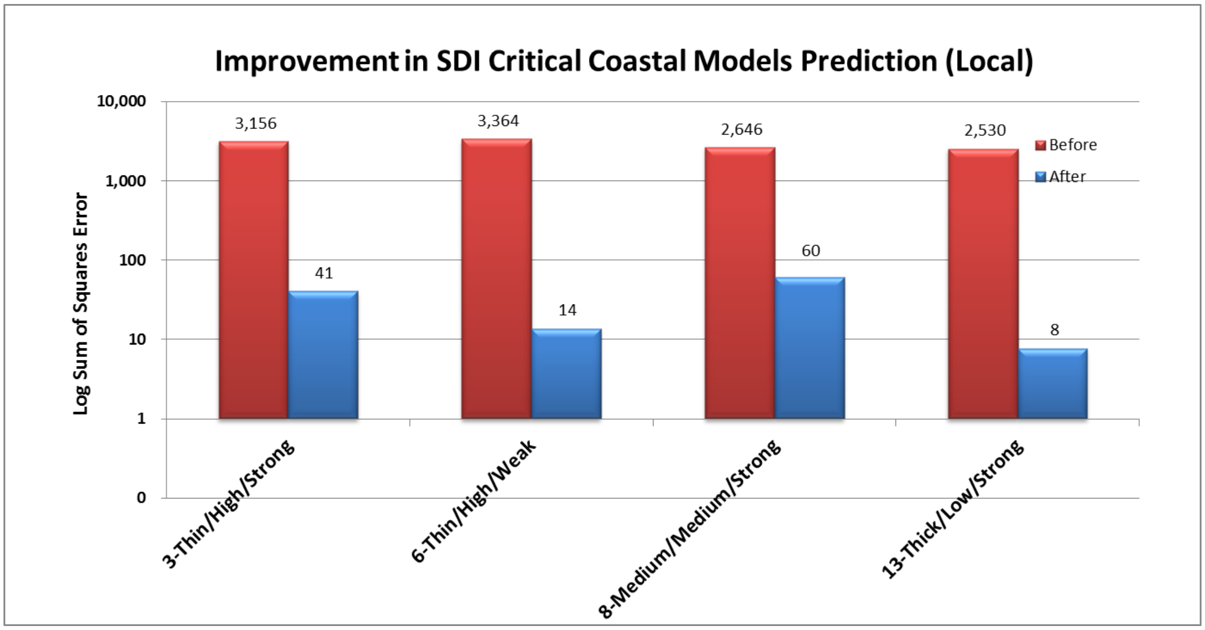


Figure 4-22: Improvement in SDI Model Prediction (Local Road)

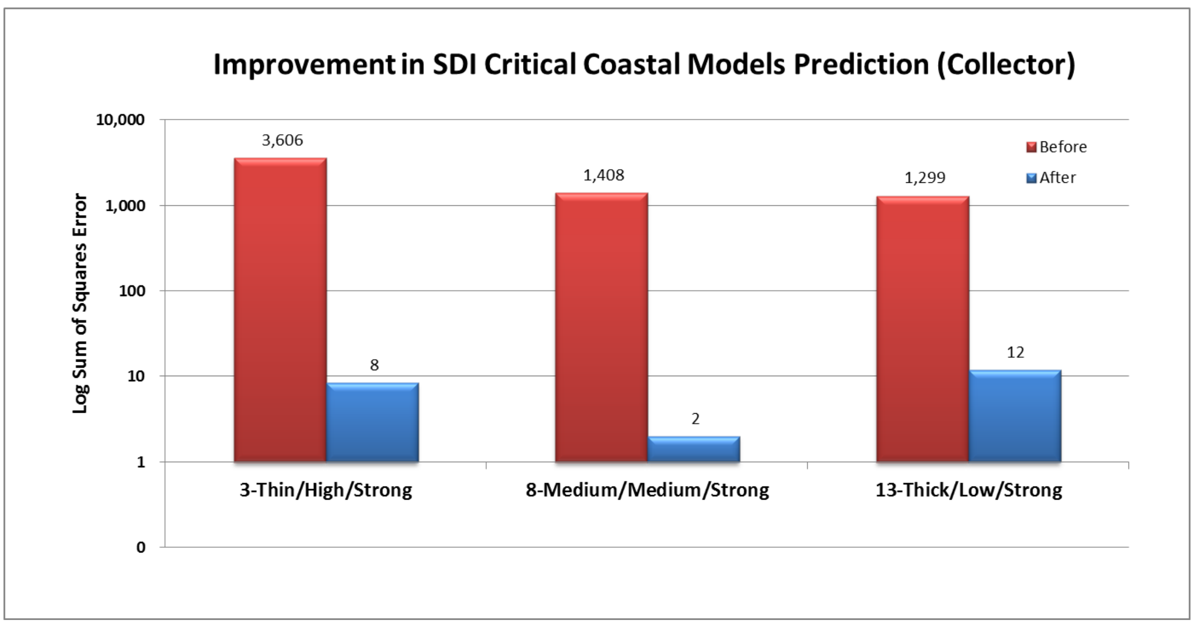


Figure 4-23: Improvement in SDI Model Prediction (Collector Road)

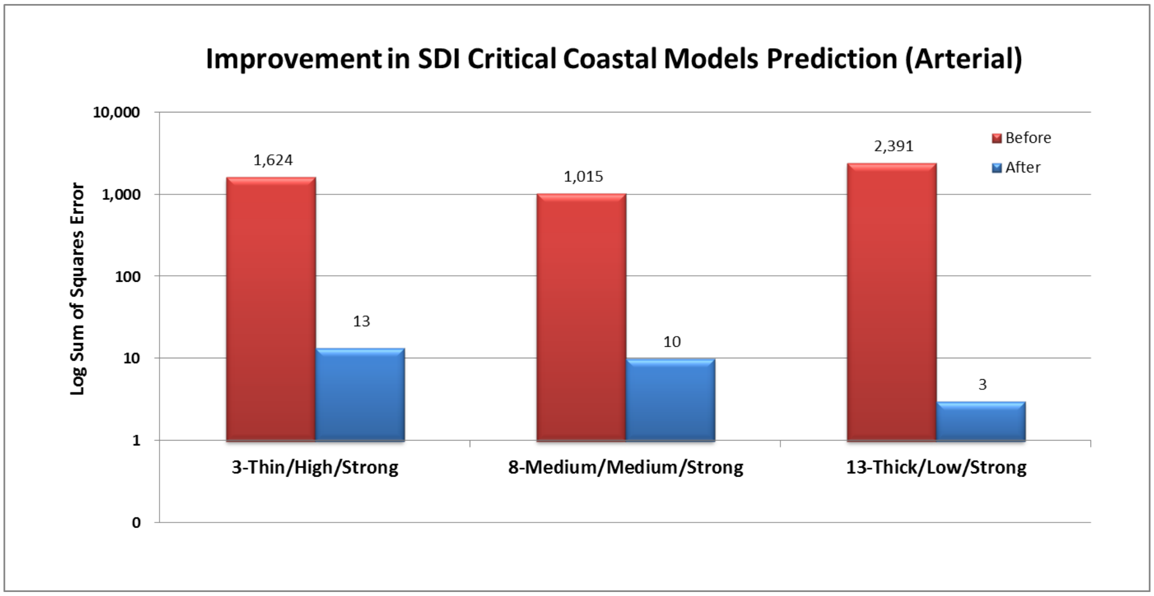


Figure 4-24: Improvement in SDI Model Prediction (Arterial Road)

4.6 CONCLUSION

The analysis in this section aims at developing enhanced empirical models for the Western Canadian region in order to better predict pavement performance. Data collected from two cities in British Columbia was used to develop models for RCI and SDI scores. Parameters known to highly impact pavement conditions were identified as traffic patterns, pavement thickness, and subgrade condition. Accordingly, the data was classified based on these factors for each functional class in the existing data. This has resulted in 18 pavement classes for each functional class, with expected service life ranges identified for each category. An optimization technique was employed to minimize the square mean error between the actual and predicted values using the constraints in the expected service life ranges. Comparison between the models developed for the western and eastern regions revealed that the RCI scores in the western region tended to deteriorate at a faster rate compared to those in the east. Variation in construction practices, along with other influencing factors such as environmental condition and traffic patterns, may have contributed to the greater rate of RCI deterioration in Western Canada as compared to the eastern region.

For the SDI index, the relatively mild weather in Western Canada extended the service life of the flexible pavement in general in comparison to that in Eastern Canada. Analysis of SDI scores revealed that the SDI scores in the Western Canadian region tended to stay in relatively better condition during the first few years, before deteriorating in a descending rate after the first few years. More condition data in Western Canada is needed to validate these findings, enhance the developed empirical models, and to represent more accurately the actual condition of pavement behaviour over time. It should be noted that western region models presented in this analysis only reflect conditions pertain to the two cites used in the analysis and in order to develop models that accurately represent the entire western Canada region, more data from other municipalities in this region is needed to be used in the development of these models. Similarly for eastern region models, the data presented in this study reflects only condition for southern Ontario where most of the data was collected, however, more data from other municipalities in eastern Canada region will definitely provide broad coverage for different conditions in eastern region. The next Chapters will focus on the development of new M-E prediction models for the Eastern Canadian region (Ontario), also considering the impact of migrating from traditional empirical to M-E models.

5.0 Mechanistic-Empirical Models Calibration

5.1 OVERVIEW OF THE MEPDG ANALYSIS AND DESIGN PROCESS

The Mechanistic-Empirical Pavement Design Guide (MEPDG) is proposed as an advanced pavement design tool that integrates up-to-date pavement practices. Major changes have been made in pavement modelling and analysis in the newly developed MEPDG when compared with the 1993 American Association of State Highway and Transportation Officials AASHTO Pavement Design Guide. Since MEPDG was first released in 2004, transportation agencies have continuously worked on calibrating and evaluating the program with regard to implementation by provincial and local agencies in Canada. The overall MEPDG objective is to provide a state-of-the-practice tool for the highway community to use in new and rehabilitated flexible pavement structure design and analysis, based on mechanistic-empirical (M-E) principles (Von Quintus 2008).

MEPDG requires three categories of data as input: traffic, climate, and pavement structure (ARA 2004) and (Zaghloul, et al. 2006). There are also three levels of data precision: Level 1 requires site-specific data, based on laboratory or field tests; Level 2 inputs are derived from other material properties measured in either the laboratory or field tests; and Level 3 is estimated from designers' experience. The MEPDG is expected to be adopted by most transportation agencies and pavement engineers in the next few years. The MEPDG program was initially implemented to provide engineers with a tool for pavement design based on M-E concepts followed by the final product M-E AASHTOWare® program. The analysis in this research started when AASHTOWare® was still under development; therefore, the MEPDG was used in the analysis. When AASHTOWare® became available, a comparison between MEPDG and AASHTOWare® predictions showed insignificant differences for LTPP sites in Ontario. Because the prediction models did not change significantly since the development of AASHTOWare®, it is not expected to produce variation in model prediction. (S. Kim, H. Ceylan and D. Ma, et al. 2014) carried out a study to locally calibrate 25 sites in Iowa, reporting insignificant differences in IRI model prediction for selected flexible pavement sections.

In order to provide a fair comparison between the empirical models developed earlier and the mechanistic empirical M-E models, the MEPDG will be used as a tool to develop realistic M-E models. These models will be the benchmark for comparison with previously developed empirical models. In order to achieve this goal, it is essential to first calibrate the MEPDG models to site-specific conditions. Specifically, M-E distress models must be locally calibrated to match up predicted results with locally measured data. Calibrating distress models inherited in the design procedure, however, has proven to be a challenging task for pavement practitioners and experts due to the complexity in processing input/output data within the MEPDG application. The dependency of models variables on other parameters that may not be available or will need different calibration process to predict makes it difficult to calibrate models outside of MEPDG context. The literature review showed that the vast majority of calibration techniques currently in use are based solely on statistical analysis and trial and error approaches, using different combinations of local calibration coefficients to find the best set that converges predicted values to data observed in the field. This approach is obviously time consuming, unpractical, and lacks accuracy, considering the limited number of trials that can be evaluated. In addition, this approach suffers from the absence of a mathematical algorithm to guide the search for the optimum solution.

This Chapter will use a genetic algorithm (GA) optimization technique to calibrate MEPDG roughness models, and ultimately develop site-specific mechanistic empirical models that can then be compared to empirical models. The framework for the calibration procedure will be designed to simulate the MEPDG calibration process within the genetic algorithm context (Ayed and Tighe 2015). Site-specific data from different locations in Ontario will be used as inputs for MEPDG, and initial calibration coefficient seeds will be introduced into the system to produce an initial output which can be compared to measured field data. The genetic algorithm will then be employed to guide the selection of new calibration sets each time an analysis cycle is performed. Crossover and mutation processes will be used to produce a new set of chromosomes, which will then be presented to the calibration system for a new evaluation cycle in an automated process to overcome the drawbacks of traditional trial and error approaches. Calibration framework design and development will be discussed in the next sections, along with the results and advantages of using the genetic algorithm approach over traditional methods.

5.2 INTRODUCTION

5.2.1 Background

Many provincial and local agencies today collect pavement condition data (e.g. rutting, cracking and IRI) using automatic road surveyors in a continuous manner. This data, often stored in PMS, indicate not only average pavement performance, but also variations in performance over time. Such data can be used in the local calibration of MEPDG design reliability, as previously reported in several studies (Wu, Yang and Zhang 2013) and (Hamdi, Tighe and Ningyuan 2014). Many studies and projects have developed methods of calibration and validation to adapt MEPDG procedure to local conditions. The following summarizes some of the efforts made in North America and internationally to locally calibrate MEPDG:

Tennessee

A study was carried out to validate MEPDG models with pavement performance data in the state of Tennessee (Zhou, et al. 2013). It was found that MEPDG was relatively conservative for highway pavements with low traffic levels. However, use of MEPDG with nationally averaged default parameters was not sensitive enough to differentiate various climates, traffic, and materials in Tennessee for the prediction of a present serviceability index (PSI). The state PMS was found to be a better source for data that can then be used for MEPDG model calibration and validation (FHWA 2010).

Iowa

Several studies were carried out in the state of Iowa using PMS data to calibrate MEPDG (S. Kim, H. Ceylan and K. Gopalakrishnan, et al. 2010), (S. Kim, et al. 2010) and (S. Kim, H. Ceylan and D. Ma, et al. 2014). A total of 70 sites from Iowa, representing both jointed plain concrete pavements (JPCP) and hot mix asphalt (HMA) pavements, were selected, and the accuracy of the nationally calibrated MEPDG prediction models for Iowa conditions was evaluated. These studies reported that local calibration of the MEPDG performance prediction models seems to have improved the accuracy of both JPCP performance predictions and HMA rutting predictions. The locally calibrated IRI model for Iowa JPCP improves the accuracy of predictions by tightening the scatter around the line of equality.

Montana

A study was carried out for the State of Montana. The objective of this study was to develop performance characteristics or variables of flexible pavements in Montana, and to use these characteristics in the implementation of the distress prediction models or transfer functions included in the MEPDG (Von Quintus and Moulthrop 2007).

Arizona

A study was conducted for the State of Arizona to implement the DARWin-ME pavement design guide (Darter, Von Quintus, et al. 2014). The study documented a practical stand-alone user's guide that provides instructions for obtaining inputs, conducting design, and establishing the recommended pavement design. The study focused on assembling DARWin-ME input data from 180 Long Term Pavement Performance and pavement management system sections of flexible, rigid, composite, and rehabilitated pavements, and calibrating the DARWin-ME distress and IRI prediction models to Arizona conditions.

Utah

Another study was carried out in Utah (Darter, Glover and Von Quintus 2009). The implementation of the MEPDG as a UDOT standard required modifications in some UDOT pavement design protocols (i.e., lab testing procedures, equipment and protocols, traffic data reporting, software issues, design output interpretation, and others). In this study, the nationally calibrated MEPDG models were evaluated. With the exception of the new hot-mix asphalt (HMA) pavement total rutting model, all models were found to be reasonable.

Indiana

A study was conducted in the state of Indiana to evaluate the application of MEPDG to Indiana conditions (Galal and Chehab 2005). The study focused on modeling and calibrating the permeant deformation to Indiana conditions. Design levels and inputs were varied to assess both the functionality of the MEPDG and the feasibility of applying M-E design concepts to the particular structural pavement design of Indiana roadways. The study also determined the sensitivity of the design parameters and input levels most critical to the MEPDG predicted distresses, as well as their impact on the implementation strategy that would be recommended to INDOT.

Ohio

A study was conduct in the Ohio (Glover and Mallela 2009) with the objective of implementing the MEPDG for the Ohio Department of Transportation (ODOT) and investigating a key requirement for integrating the MEPDG into current ODOT pavement design procedures, that is, evaluating the adequacy of global calibration factors for predicting pavement performance in Ohio and, if needed, developing local calibration factors. The study found that the prediction capacities of the MEPDG new hot mix asphalt (HMA) rutting and smoothness (IRI) models, and the new jointed plain concrete pavement (JPCP) IRI model needed to be calibrated for Ohio conditions.

Arkansas

A study was conducted in the state of Arkansas (Hall, Xiao and Wang 2011). In this study, the procedure for local calibration of the MEPDG was established using LTPP and PMS. The study concluded that thermal cracking should be specifically identified in a transverse cracking survey to calibrate the transverse cracking model in MEPDG. Calibration coefficients were optimized for the alligator cracking and longitudinal cracking models in this study, both of which were improved by calibration.

Texas

A study was carried out in Texas (Banerjee, et al. 2009), with the objective of producing guidelines for local calibration of the MEPDG. Regional calibration factors were obtained by minimizing the sum of squared errors between the observed and the predicted distresses, while the average of the regional calibration coefficients for AC and subgrade rutting was computed to obtain a set of state-default calibration coefficients for Texas.

Washington

A study conducted in the state of Washington (Li, Pierce and Uhlmeyer 2009) presented WSDOT's latest efforts at calibrating the flexible pavement portion of MEPDG with data obtained from the Washington State PMS. The study concluded that the flexible pavement distress models were calibrated successfully, and that WSDOT flexible pavements require local calibration that differs from the defaults. A software bug was reported in this study that did not allow calibration of the roughness model for local Washington conditions.

North Carolina:

A study carried out in North Carolina presented the calibration of the MEPDG for flexible pavements located in the state (Muthadi and Kim 2008). The standard error for the HMA permanent deformation model, as well as for the alligator cracking model, was found to be significantly less than the global standard error after calibration. It was decided that both models would be kept for a more robust calibration in the future that would increase the number of sections and include more detailed inputs (mostly Level 1 inputs).

International:

A number of studies conducted at the international level have implemented an MEPDG calibration adapted to the traffic conditions, climate and material resources of each particular country. Research has been undertaken in India (Ghosh, Padmarekha and Murali 2013), Korea (Suh, Cho and Mun 2011), China (Zhang, et al. 2015), Chile (Delgadillo, Wahr and Alarc´on 2011), Peru (Romero, Garro and Zevallos 2016) and South Africa (Anochie-Boateng and Maina 2012). Most of these studies attempted to calibrate MEPDG to local conditions using a trial and error approach to close the gap between measured and predicted pavement performance.

5.2.2 Roughness Model

Within the MEPDG context, functional performance for all pavements types is defined by time (pavement age), dependent on pavement roughness, which is quantified as a predicted International Roughness Index (IRI). IRI is predicted using a regression equation with computed pavement distresses, initial IRI, and “site/climate” factors as the primary independent variables (Li, Mills and McNeil 2011). The roughness model in MEPDG design for overlay of flexible pavement is measured using the following equations:

$IRI = IRI_0 + 0.011505\ (Age) + 0.0035986\ (FC)_T + 3.4300573\left(\frac{1}{(TC_S)_{MH}}\right) + 0.000723(LC_S)_{MH} +$

$0.0112407(P)_{MH} + 9.04244(PH)_T$ ... . (Equation 5.1) (ARA 2004)

where:

IRI_o	*= Initial IRI measured within six months after construction, m/km*,
Age	*= Age after construction, years,*
$(FC)_T$	*= Total area of fatigue cracking (low, medium, and high severity levels), percent of wheel path area, %.*
$(TC_S)_{MH}$	*=Average spacing of medium and high severity transverse cracks, m.*
$(LC_S)_{MH}$	*= Medium and high severity sealed longitudinal cracks in the wheel path, m/km.*
$(P)_{MH}$	*= Area of medium and high severity patches, percent of total lane area, %.*
$(PH)_T$	*= Pot holes, percent of total lane area, %.*

As shown in the previous equations, the independent variables are correlated to parameters related to other distresses that are being predicted/calculated within the MEPDG environment; the IRI model cannot therefore be calibrated outside of the MEPDG using these equations, and MEPDG needs to be executed iteratively to calculate all inputs needed for the IRI model.

5.3 MEPDG CALIBRATION TECHNIQUES

5.3.1 Scope and limitation for calibrated models

The literature review revealed that variables such as age, traffic, subgrade condition, road functional class, and pavement thickness are the most significant factors in IRI deterioration models (Baus. and Stires 2010). Therefore, selected sections from various Ontario municipalities' PMS databases will be classified for the study based on the design of experiment (DOE) that accounts for factors known to highly influence pavement performance. Three sections in each DOE class are selected to represent different functional classes for local, collector and arterial roads, respectively, as shown in Table 5-1. In some conditions, no matching sections were found in the database to represent a particular condition. For example, no local sections (0) were found in the medium thickness, weak subgrade, and low traffic category, and only collector and arterial sections were used (0, 1, 1). Material, traffic and site specific inputs for selected sections were collected from different PMS databases and entered into MEPDG, with a total of 42 MEPDG design models were prepared for each section.

Table 5-1: Number of Sections with Records for different DOE Classes

Index	Thickness	Subgrade	Traffic		
			Low	Medium	High
RCI	Thin	Weak	0, 1, 0	0, 0, 1	1, 1, 1
		Strong	1, 0, 1	0, 1, 1	1, 0, 0
	Medium	Weak	0, 1, 1	0, 1, 1	0, 1, 1
		Strong	1, 1, 1	1, 1, 1	1, 1, 1
	Thick	Weak	1, 1, 1	1, 1, 1	1, 1, 1
		Strong	1, 1, 1	1, 0, 1	1, 1, 1

5.4 PROBLEM STATEMENT

The literature review showed that most research efforts aimed at calibrating MEPDG models, including roughness, are accomplished mainly based on a "trial and error" statistical approach. In other words, local roughness calibration coefficient sets (C1, C2, C3 and C4) are initially introduced to MEPDG, calculated IRI output is compared to measured IRI, and the deference is evaluated against a predefined benchmark. Different combinations of calibration coefficient sets are entered a number of times, and the set with the least difference is selected as the best set for a particular condition. This approach lacks the mathematical logic to guide the search for a new calibration set based on the previously selected set of results.

Optimization algorithms, including genetic algorithms, are suitable to solve these problems where a guiding engine is employed to direct the search to the optimum solution. (Jadoun and Kim 2012) attempted to use the genetic algorithm to calibrate rut and alligator crack in MEPDG. The study used an apads.exe (Jadoun and Kim 2012) engine module included in MEPDG to predict future distresses. This module cannot be used outside the MEPDG context, however, and a special software module was developed just for this study in order to have apads.exe work as a standalone module. It cannot therefore be used for other studies or research.

5.5 METHODOLOGY

To overcome this problem, a genetic algorithm (GA) framework is prepared to optimize calibration coefficients. Initial trials attempt to use linear programming optimization approach included with Microsoft Excel software (Solver), however, MEPDG outputs results are in excel format which conflict and prevent excel solver from executing repetitive trials. Therefore, a genetic algorithm programed using Visual Basic platform was developed to have a full control of the optimization process. The GA framework implementation includes an MEPDG Engine that receives initial coefficient seeds for C1, C2, C3 and C4 from GA, calls MEPDG application, opens a calibration screen for IRI (as shown in Figure 5-1), inserts the parameters, executes the analysis based on the passed coefficients, closes the MEPDG application, and finally reads the results file to obtain the predicted IRI at different ages. It was essential to automate this process so that it can be included in an iterative process later, within a genetic algorithm framework as explained in the next section.

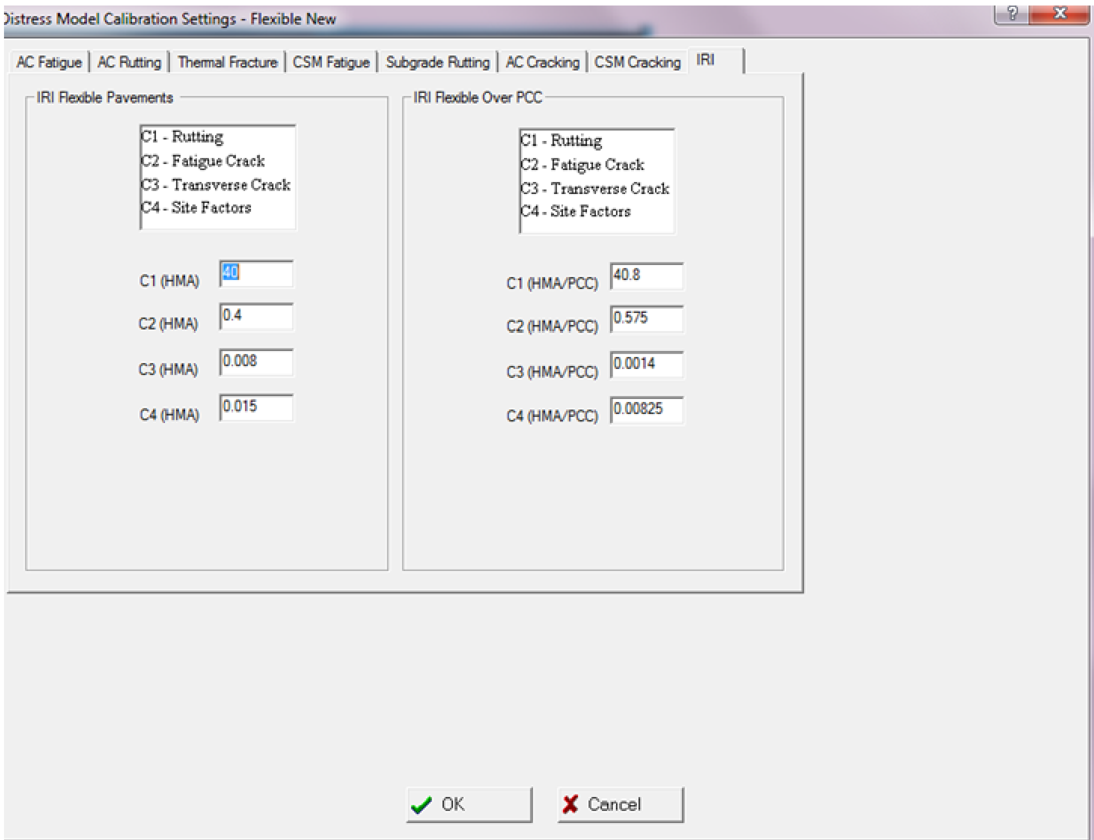


Figure 5-1: MEPDG Screen for entering Roughness Calibration coefficients

5.6 RCI BACKCALCULATION

The roughness database is stored in PMS as a Riding Comfort Index (RCI). In order to calibrate the MEPDG, the data needs to be converted into actual measured roughness in inch/mile units. The transfer function used to by the Ministry of Transportation of Ontario (MTO) (used in the PMS-2 to reflect pavement roughness) was therefore utilized to convert scaled (0 to 10) RCI values to measured IRI values for flexible pavement (Li, Kazmierowski, et al. 2001).

$$RCI = 8.52 - 7.49\,\log_{10}(\text{IRI}) \quad \text{.............................(equation 5.3)}$$

5.7 MEPDG LOCAL CALIBRATION USING GENETIC ALGORITHMS

5.7.1 Overview of Genetic Algorithms (GA)

Genetic algorithms (GA) are inspired by Darwin's theory of evolution. The ways in which genetic algorithms are used to solve mathematical problems and find optimum solutions. An algorithm is started with a set of solutions (represented by chromosomes) called a population. Solutions from one population are taken and used to form a new generation. This is motivated by the hope that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness. The more suitable they are, the more chances they have to reproduce. This is repeated until some condition (for example the number of populations or improvement of the best solution) is satisfied. GAs have been successfully used to solve many optimization problems in the pavement industry (Golroo and Tighe 2012). This includes solving multi-objective maintenance and rehabilitation programming problems at both the project and network level of analysis (Chikezie, Olowosulu and Abejide 2013) and (Morcousa and Lounisb 2005).

5.7.2 Modeling Approach

Genetic algorithm is employed in this study to locally calibrate IRI models included in the MEPDG. As shown in Figure 5-2, the process starts by randomly generating four initial seeds (chromosomes) for calibration coefficients, with each chromosome consists of C1, C2, C3 and C4, representing different combinations of calibration coefficients. Subsequently each chromosome is introduced to the automated MEPDG engine to execute the analysis and store roughness results in a database, to be used later as well as to be passed back to the GA. The advantage of storing analysis results is the possibility that they can be used again if the same chromosome is either chosen later or generated randomly as part of a new generation, which will save the MEPDG reprocessing time. The genetic algorithm calculates the fitness of each chromosome using the following equations:

$$Fitness = \frac{Calculated\ Roughness}{Measured\ Roughness} * \ 100\ (where\ Calculated\ Roughness > Measured\ Roughness)$$
…………………………………………………………………………………………..(Equation 5.2)

$$Fitness = \frac{Measured\ Roughness}{Calculated\ Roughness} * \ 100\ (where\ Calculated\ Roughness < Measured\ Roughness)$$
……..…………………………………………………………………………………………(Equation 5.3)

The closer the fitness is to 100%, the more the chromosome has a chance of surviving for the next generation. The next step is to identify the best and worst chromosomes in the current generation. The worst performing chromosome(s) will be killed to leave room for offspring generated as a result of crossover and mutation by the best chromosomes. Next, the fittest parent pair is selected to generate new offspring by crossover. Mutation of single chromosome gene was performed on a random base only when a random mutation rate exceeded 25%. Mutation of all chromosomes was applied when all chromosomes had the same fitness. Fitness for the new generation chromosomes was evaluated again, and the process was repeated until the fitness met the predefined target level, which is in this case was an accuracy greater than 95%. Figure 5-3 shows the interface for the genetic algorithm program that has been developed to calibrate the MEPDG roughness.

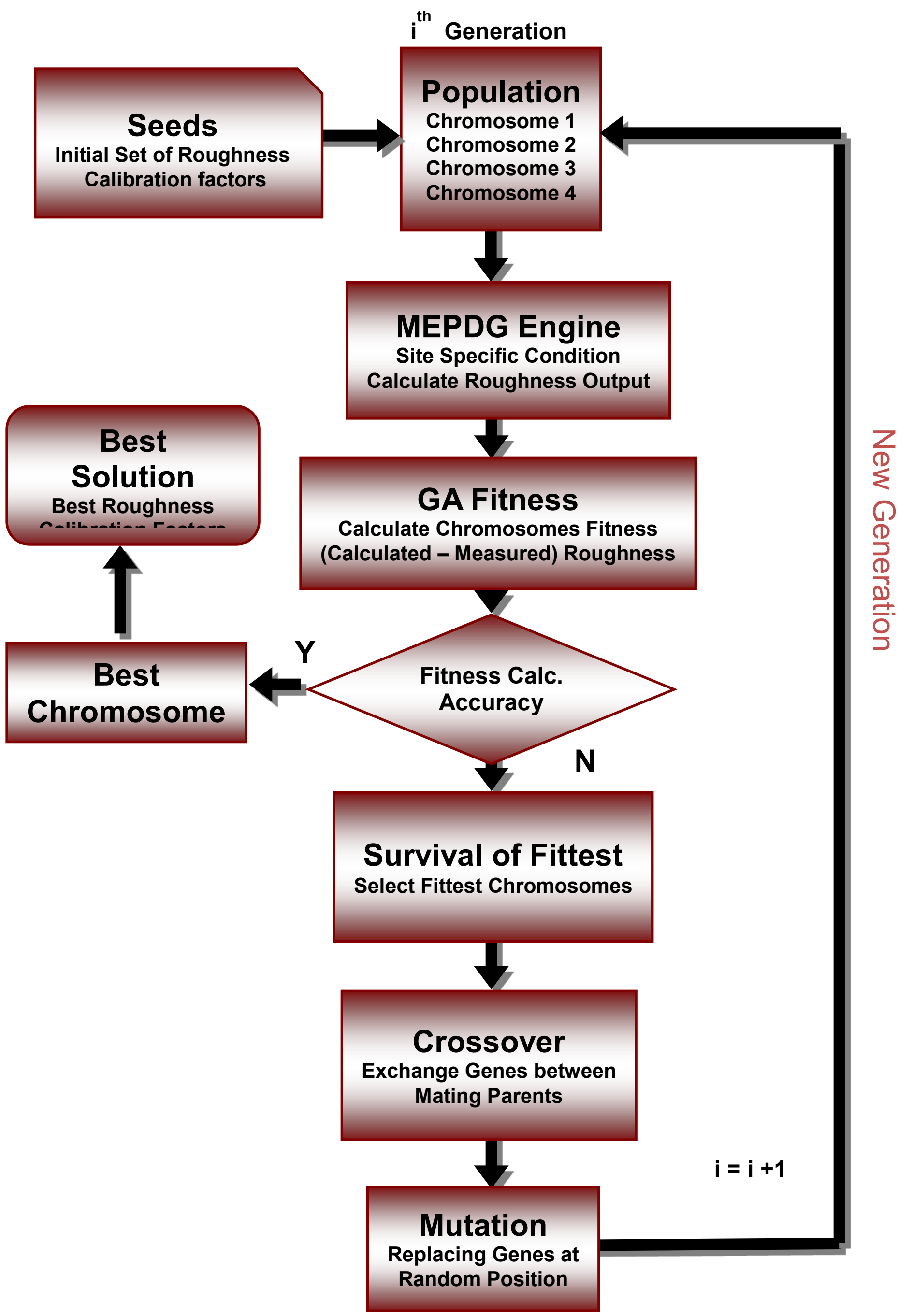


Figure 5-2: Framework for Genetic Algorithm used in the Calibration

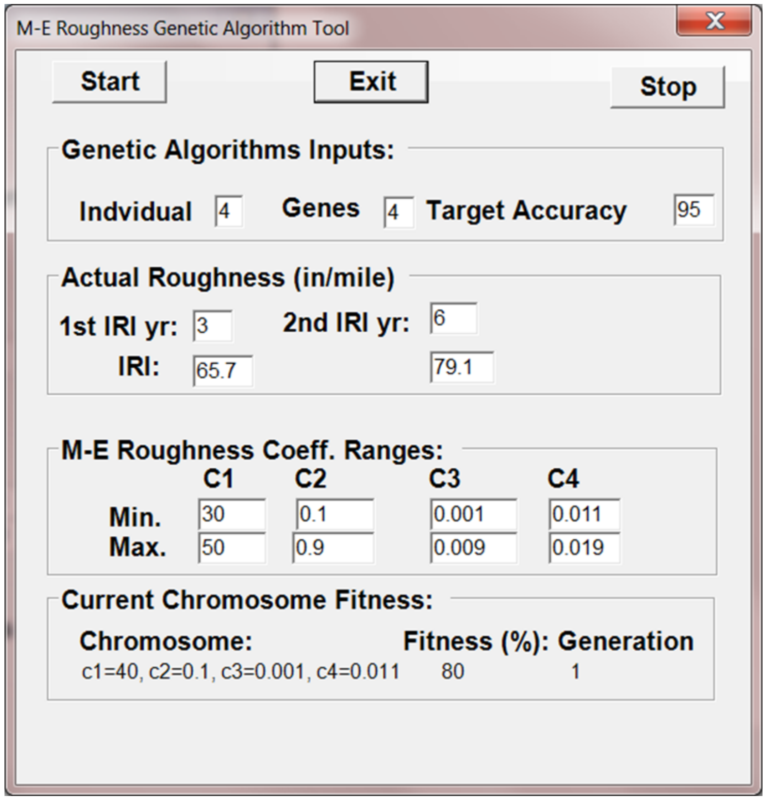


Figure 5-3: Screenshot from Developed Genetic Algorithm Tool for Roughness Calibration

5.8 RESULTS

Table 5-2 shows the results for the fittest chromosomes for each DOE category. For example, three sections with the functional classes of local, collector and arterial, respectively, were calibrated for thin thickness, weak subgrade and high traffic. The best fitness achieved for each section was 92%, 90% and 74% respectively. Categories where no section was found in the PMS database were designated with NA results. Table 3 shows the details for each section optimum solution, along with the measured IRI and the calculated IRI resulting from the GA. As can be seen in Table 5-2 and Table 5-3, the majority of chromosomes for selected sections showed fitness above 90%, with a slight difference between predicted and measured roughness, suggesting that GA is a promising tool that can be used to locally calibrate MEPDG distress coefficients. Few sections showed low fitness (below 90%), however, the fitness can be improved by changing the mutation rate (and/or crossover positioning) to produce a more fit solution to the problem.

Table 5-2: Fitness Results for MEPDG Roughness Calibration

Thickness	Subgrade	Traffic		
		Low	Medium	High
Thin	Weak	NA, 96, NA	NA, NA, 93	92, 90, 74
	Strong	54, NA, 94	NA, 97, 96	95, NA, NA
Medium	Weak	NA, 94, 95	NA, 93, 74	NA, 83, 89
	Strong	89, 85, 84	91, 92, 82	92, 93, 84
Thick	Weak	93, 95, 95	95, 92, 93	93, 87, 59
	Strong	78, 81, 97	93, NA, 90	97, 90, 92

Table 5-3: Calibration Results for each Selected Section in the DOE

F.Class	Thickness	Subgrade	Traffic	C_1	C_2	C_3	C_4	Fitness %	Measured IRI		GA IRI	
									1	2	1	2
Local	Thin	Strong	Low	42	0.8	0.003	0.018	54.2	170.5		92.5	
	Thin	Strong	High	43	0.6	0.004	0.017	94.9	95.1		90.2	
	Thin	Weak	High	38	0.6	0.006	0.016	92.2	110.9		102.2	
	Medium	Strong	Low	49	0.4	0.008	0.019	89.0	101.1	114.3	94.1	97.1
	Medium	Strong	Medium	47	0.7	0.005	0.019	91.4	141.8	165.3	138.1	141.3
	Medium	Strong	High	44	0.3	0.001	0.017	92.3	92.2	107.5	90.1	93.4
	Thick	Strong	Low	50	0.8	0.005	0.017	77.8	114.3		88.9	
	Thick	Strong	Medium	33	0.5	0.001	0.014	93.4	125.4		134.2	
	Thick	Strong	High	47	0.5	0.003	0.016	97.0	69.9	79.1	71.4	75.9
	Thick	Weak	Low	50	0.1	0.007	0.019	93.2	146.2		136.2	
	Thick	Weak	Medium	36	0.2	0.008	0.011	94.7	117.9		124.5	
	Thick	Weak	High	31	0.1	0.008	0.016	92.8	54.7	67.8	63.7	68.1
Collector	Thin	Strong	Medium	43	0.3	0.001	0.014	97.1	63.8		61.9	
	Thin	Weak	Low	39	0.4	0.002	0.015	96.3	117.9		122.4	
	Thin	Weak	High	43	0.3	0.001	0.015	90.2	146.2		131.9	
	Medium	Strong	Low	46	0.7	0.005	0.019	84.6	170.5	231.9	164.4	168.6
	Medium	Strong	Medium	38	0.3	0.001	0.015	92.0	165.3	175.8	155.1	158.6
	Medium	Strong	High	50	0.4	0.003	0.015	92.9	110.9	137.5	129.2	137.4
	Medium	Weak	Low	42	0.4	0.006	0.018	94.3	110.9	133.3	121.8	130.1
	Medium	Weak	Medium	40	0.9	0.002	0.015	92.7	101.1	121.6	116.6	123.3
	Medium	Weak	High	46	0.8	0.005	0.012	82.6	65.7	79.1	83.8	91.0
	Thick	Strong	Low	46	0.2	0.005	0.017	81.0	98.0	110.9	82.8	86.0
	Thick	Strong	High	30	0.6	0.004	0.012	90.5	117.9	129.3	133.6	139.5
	Thick	Weak	Low	37	0.4	0.001	0.018	94.6	110.9	129.3	111.3	115.8
	Thick	Weak	Medium	44	0.2	0.009	0.017	91.9	192.8	198.8	177.1	182.7
	Thick	Weak	High	44	0.6	0.004	0.018	87.2	81.5	117.9	103.3	112.5
Arterial	Thin	Strong	Low	38	0.8	0.001	0.011	93.7	150.8		160.6	
	Thin	Strong	Medium	48	0.1	0.008	0.013	96.2	137.5		143.0	
	Thin	Weak	Medium	49	0.4	0.006	0.019	92.8	155.5	165.3	143.1	154.7
	Thin	Weak	High	38	0.4	0.007	0.011	73.5	72.1	98.0	104.4	125.6
	Medium	Strong	Low	45	0.5	0.007	0.019	83.9	95.1	98.0	79.2	82.8
	Medium	Strong	Medium	46	0.8	0.002	0.018	81.5	155.5	165.3	127.8	133.7
	Medium	Strong	High	44	0.6	0.007	0.018	83.9	117.9	117.9	98.9	
	Medium	Weak	Low	46	0.3	0.001	0.018	94.7	110.9	117.9	103.2	113.6
	Medium	Weak	Medium	46	0.3	0.009	0.017	74.4	146.2	192.8	119.0	130.0
	Medium	Weak	High	45	0.4	0.002	0.018	89.3	137.5	165.3	128.9	140.2
	Thick	Strong	Low	40	0.4	0.002	0.016	96.6	133.3	146.2	136.2	139.3
	Thick	Strong	Medium	41	0.4	0.006	0.018	90.0	146.2	155.5	133.7	137.7
	Thick	Strong	High	36	0.3	0.001	0.018	91.9	121.6	150.8	123.2	128.2
	Thick	Weak	Low	35	0.3	0.001	0.017	95.0	110.9	133.3	115.6	125.4
	Thick	Weak	Medium	32	0.5	0.007	0.011	93.4	76.7	86.7	84.4	90.5
	Thick	Weak	High	49	0.4	0.006	0.018	58.8	150.8		88.6	

5.9 COMPARISON BETWEEN EMPIRICAL MODELS AND MECHANISTIC EMPIRICAL MODELS

In order to provide a fair comparison between existing empirical models and the M-E models, the sections used in M-E genetic optimization calibration were individually entered into the same process presented in Chapter 3, in order to develop deterioration models for these sections. The resulting roughness values for each of the 42 M-E models were backcalculated to RCI values using the MTO models utilized in section 5.6. The RCI values were scaled back overtime using the years from initial values for IRI before optimization was carried out. In this optimization process, the IRI results from MEPDG analysis were used as the measured parameters, and the objective function was to find the coefficients A, B and C that minimized error between measured and predicted parameters. Table 5-4 shows the final coefficients for models developed based on M-E modeling. In most of the cases, when compared to empirical models shown in Table 3-12, it can be noted that empirical models under-predict pavement condition over time compared to models based on M-E principles. This means empirical models tend to predict shorter service life compared to M-E models. For example, Table 3-12 shows that the empirical model for thin/low/strong (Model 1 for local roads) has a shorter predicted service life (19 years) compared to the corresponding model based on M-E principles (26 years). In other cases, the empirical models over-predict pavement service life compared to M-E models, as shown in Figure 5-8 where the M-E model for Thick/Low/Strong (Model 13 for collector roads) has a shorter predicted service life (26 years) compared to the empirical model (29 years) under the same conditions. Figure 5-4 to Figure 5-9 show the developed M-E models and predicted service life for critical models when compared to empirical models. Four of the critical model conditions showed that empirical models under-predict pavement condition over time, while other conditions, such as model 3 and model 6 for local roads, showed the same predicted service life.

Table 5-4: RCI Models Coefficients for Mechanistic-Empirical Modeling

Model ID	Thickness	Traffic	Subgrade	RCI Model Coefficients											
				Local				Collector				Arterial			
				a	b	c	Age	a	b	c	Age	a	b	c	Age
1	Thin	Low	Strong	4.93	11.56	2.10	26.5	NA	NA	NA	NA	4.51	8.58	2.20	19.6
2	Thin	Med.	Strong	NA	NA	NA	NA	4.91	12.25	2.20	21.3	4.50	6.64	2.10	17.0
3	Thin	High	Strong	4.87	10.11	2.15	21.7	NA	NA	NA	NA	NA	NA	NA	NA
4	Thin	Low	Weak	NA	NA	NA	NA	4.53	6.08	2.11	17.1	NA	NA	NA	NA
5	Thin	Med.	Weak	NA	NA	NA	NA	NA	NA	NA	NA	4.50	5.39	2.12	12.5
6	Thin	High	Weak	4.68	6.27	2.16	15.2	4.50	4.55	2.10	12.6	4.50	4.77	2.15	10.1
7	Med.	Low	Strong	4.71	12.00	2.15	34.5	4.52	9.95	2.20	28.3	4.60	11.22	2.17	25.5
8	Med.	Med.	Strong	4.60	10.02	2.20	30.0	4.59	9.90	2.20	25.1	4.62	9.91	2.20	20.0
9	Med.	High	Strong	5.00	10.00	2.16	17.9	4.71	10.01	2.20	21.3	4.72	10.03	2.20	17.9
10	Med.	Low	Weak	NA	NA	NA	NA	4.84	10.00	2.20	17.9	4.73	10.05	2.20	17.9
11	Med.	Med.	Weak	NA	NA	NA	NA	4.85	10.00	2.20	17.5	4.90	9.93	2.19	14.7
12	Med.	High	Weak	NA	NA	NA	NA	5.00	8.74	2.20	12.5	4.50	5.09	2.10	11.9
13	Thick	Low	Strong	4.55	10.01	2.20	33.1	4.95	15.04	2.20	26.4	4.50	10.56	2.19	26.5
14	Thick	Med.	Strong	4.54	10.12	2.20	34.5	NA	NA	NA	NA	4.62	9.98	2.20	20.2
15	Thick	High	Strong	5.00	11.45	2.17	21.0	4.50	6.64	2.10	21.0	4.70	10.09	2.20	18.5
16	Thick	Low	Weak	4.64	10.01	2.20	27.8	4.65	9.99	2.20	23.1	4.60	10.09	2.20	21.0
17	Thick	Med.	Weak	4.72	9.96	2.20	24.2	4.83	9.92	2.20	17.9	4.87	10.00	2.10	17.9
18	Thick	High	Weak	5.00	9.06	2.20	14.7	4.87	10.00	2.20	17.1	5.00	10.32	2.20	13.7

Note: NA refers to models where no enough data was available to produce models

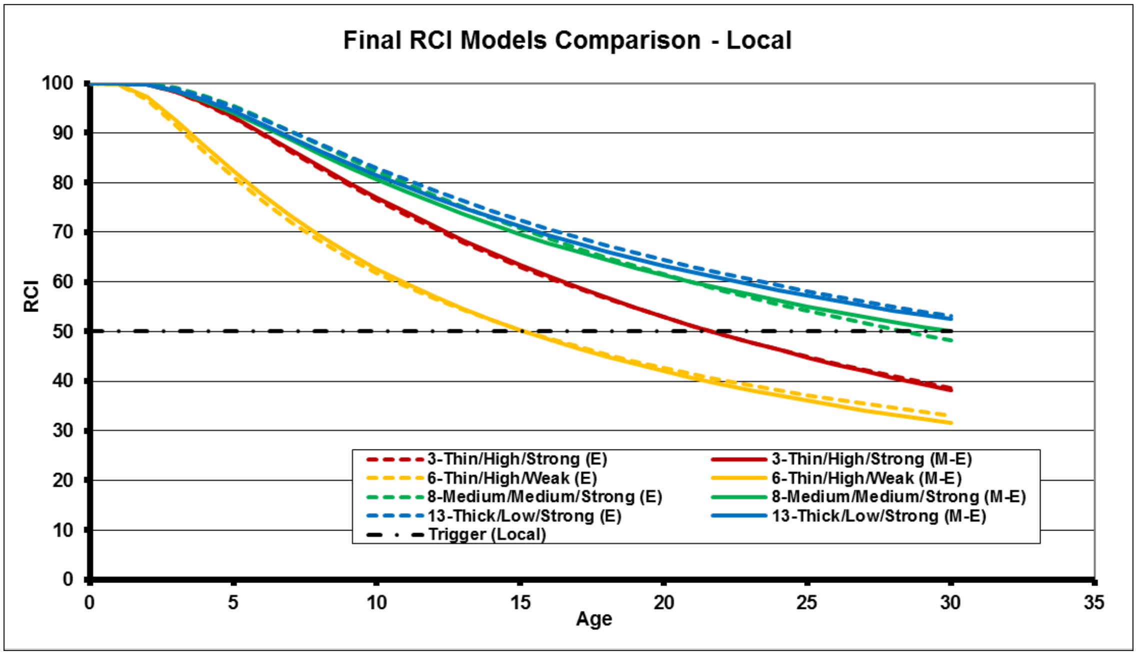


Figure 5-4: Empirical (E) vs. Mechanistic-Empirical (M-E) (Critical Models - Local)

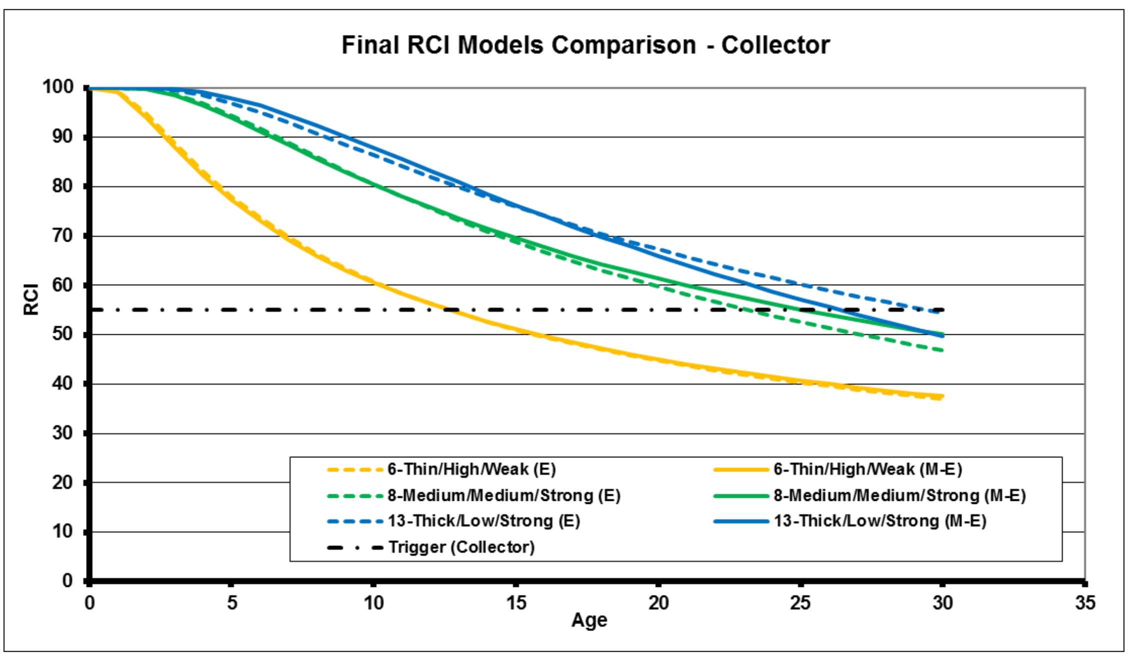


Figure 5-5: Empirical (E) vs. Mechanistic-Empirical (M-E) (Critical Models - Collector)

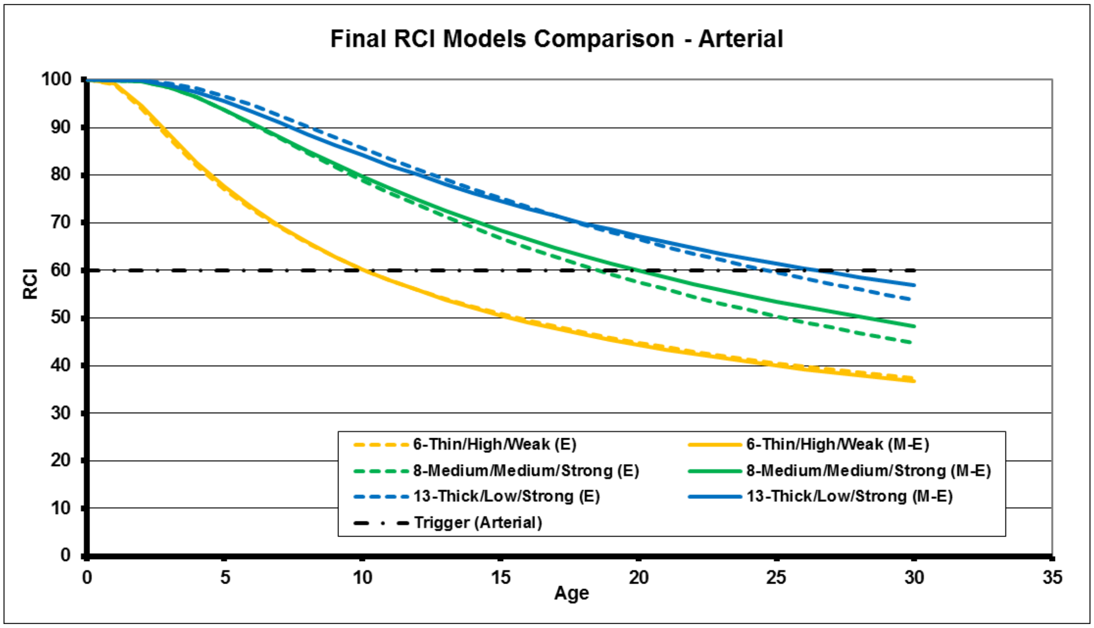


Figure 5-6: Empirical (E) vs. Mechanistic-Empirical (M-E) (Critical Models - Arterial)

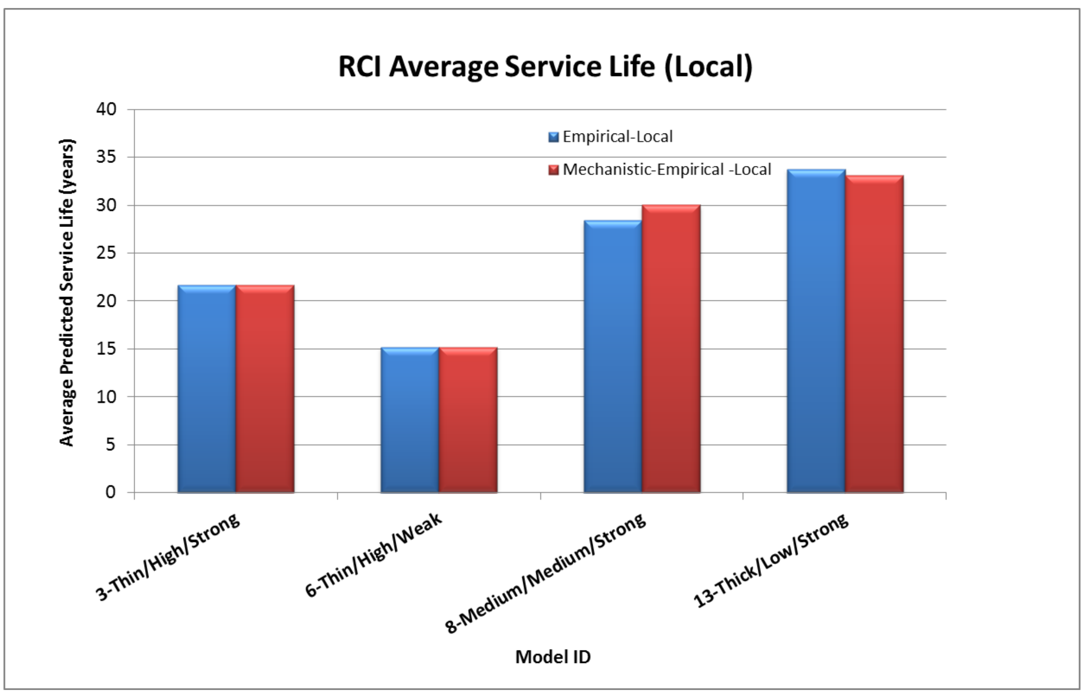


Figure 5-7: Service Life Empirical (E) vs. Mechanistic-Empirical (M-E) (Local)

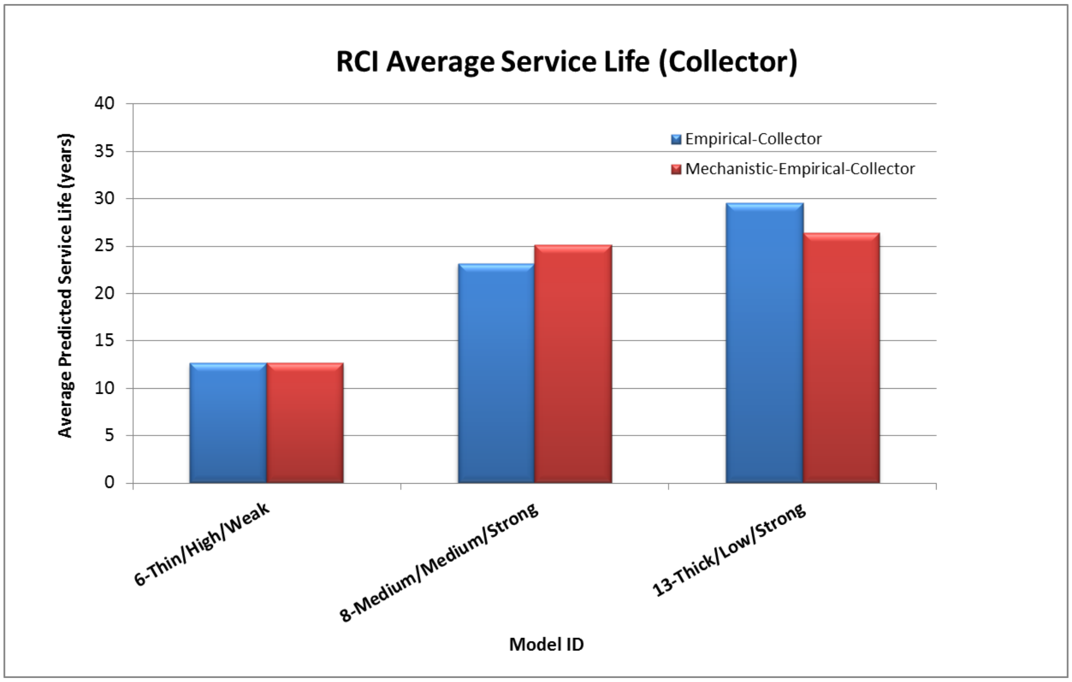


Figure 5-8: Service Life Empirical (E) vs. Mechanistic-Empirical (M-E) (Collector)

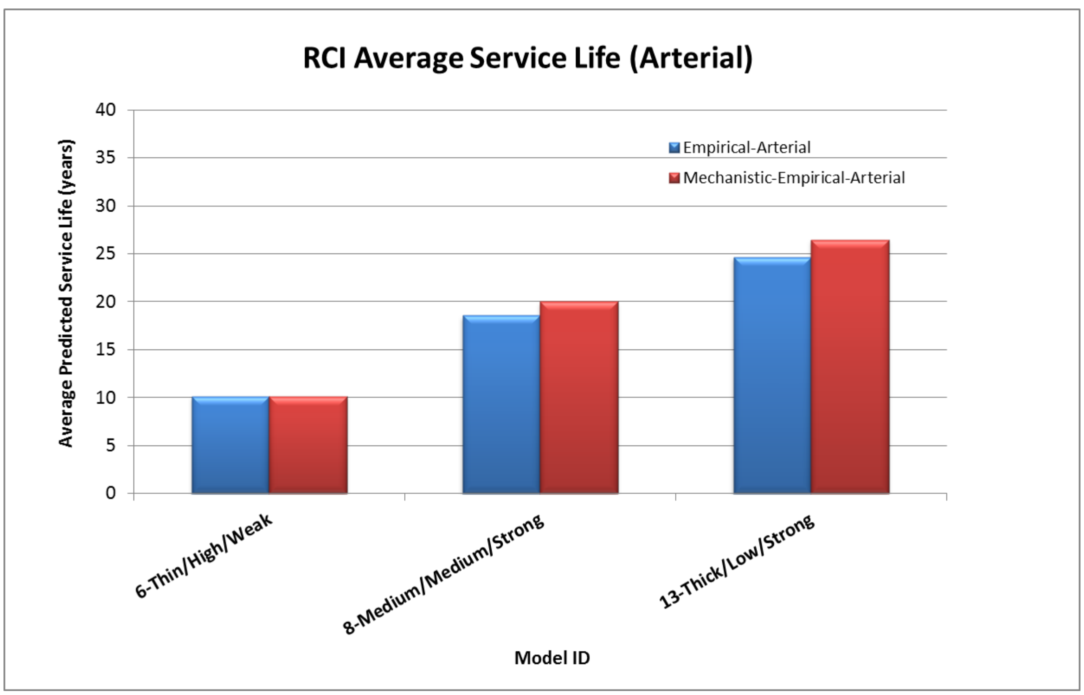


Figure 5-9: Service Life Empirical (E) vs. Mechanistic-Empirical (M-E) (Arterial)

5.10 CONCLUSION

It can be concluded that models based on M-E principles will not necessarily always overestimate pavement service life; however, it most pavement practitioners and transportation experts believe that M-E models are built on more reliable and accurate principles compared to those built on only empirical principles. The previous analysis indicated that in most cases, the empirical model underestimated the service life of the pavement. While this might provide unnecessary improvement to pavement condition by applying rehabilitation activities earlier than expected, it might also create more expenditure for transportation agencies due to an underestimated shorter service life. The next Chapters will discuss the application of M-E models at the project and network level of analysis, as well as the impact of using these models compared to traditional empirical models.

6.0 Decision-Making Framework for Rehabilitation Alternative Selection using M-E Models at Project Level Analysis

6.1 INTRODUCTION

As previously explained, performance models are used in PMS in order to predict future pavement performance, and hence identify the time needed for the next rehabilitation. The use of performance models starts at the project level, when rehabilitation alternatives are selected based on pavement performance over time. The frequency of selecting pavement rehabilitation within certain time frames will certainly impact the associated yearly cost incurred by such a strategy, as well as strategy selection at an early stage of program planning and construction. In order to validate the M-E models developed in the previous section and weigh their impact compared to empirical models, they need to be evaluated at the project level through a life cycle cost analysis (LCCA).

A comprehensive decision-making tool is implemented to carry out detailed LCCA and to facilitate selection of the appropriate rehabilitation strategy, based on site-specific conditions. The developed tool has the capability to carry out LCCA using both empirical models and M-E models simultaneously. This feature can help pavement practitioners and transportation agencies evaluate different competing rehabilitation strategies based on prediction models used in the cost analysis, and select the most cost-effective strategy based on both economic analysis and confidence in the data originally used to develop these models. Using the developed LCCA tool, city staff can enter project-specific parameters and quickly have a print out of feasible treatments, along with the corresponding life cycle cost analysis for each of these treatments.

6.2 SCOPE OF COMPARISON

It should be noted that these M-E models were only developed for flexible pavement; therefore, the decision-making tool for alternative selection considers only asphalt concrete rehabilitation options. However, this tool can be expanded to account for other pavement types. In addition, the decision-making tool only considers previously developed Ride Comfort Index (RCI) models in the deterioration condition of the pavement. If mechanistic-empirical models are to be developed in the future for other performance indexes, such as SDI, they should be incorporated into this decision tool through an overall pavement quality index (PQI), that includes both RCI and SDI. The use of PQI will provide better and more realistic pavement performance over time, and hence provide more accurate estimation for alternative rehabilitation costs. This Chapter will provide comprehensive details about the economical principles used in the development of decision-making frameworks for rehabilitation selection. The next Chapter will describe the implementation of an automated decision-making tool that incorporates the decision framework discussed herein. The automated tool can be used as a standalone tool to compare competing rehabilitation strategies, regardless of performance models used, even though it was only originally developed to compare the two performance model types (empirical vs. mechanistic-empirical).

6.3 ECONOMIC ANALYSIS AND PROGRAMMING

6.3.1 Life Cycle Cost Analysis Modeling

In this section, the economic LCCA is carried out with the objective of defining the budget requirements needed for sustainable pavement performance using different performance models. LCCA builds on well-founded principles of economic analysis to evaluate the overall long-term economic efficiency of competing alternatives for investment options. The main objectives of performing the LCCA are:

- To present an economically sound approach justifying the budget needed for sustainable pavement conditions.
- To evaluate the cost-effectiveness of different options among competing maintenance and rehabilitations (M&R) strategies.
- To identify the upper and lower bounds of expected expenditures over the analysis period, based on the uncertainty of the analysis inputs.

6.4 DECISION-MAKING FRAMEWORK ANALYSIS ASSUMPTIONS

6.4.1 Analysis Period and Economic Indicators

The analysis period used in this study extends over 50 years, where each M&R strategy includes at least one complete alternative M&R strategy. However, since this would result in M&R strategies with un-equal service lives, the economic indicator used to compare these alternatives is the Equivalent Uniform Annual Cost (EUAC) (Farashah and Tighe 2014) and (TAC 2013). The EUAC represents all costs of an M&R strategy as if they occurred uniformly throughout the analysis period. It is evaluated by first determining the Net Present Worth (NPW) of the M&R strategy using the following equation:

$$NPW = \sum_{t=0}^{N} \frac{C}{(1+i)^t} \qquad \text{(equation 6.1)}$$

Where:

NPW is the total net present worth of the strategy over the analysis period

C is the annual incurred cost at year t

i is the discount rate

t is the current year

N is the analysis period (50 years)

The EAUC is used to calculate the regular annuity, given the present worth and is calculated as follows:

$$EAUC = NPW \frac{i(1+i)^N}{(1+i)^N-1} \qquad \text{(equation 6.2)}$$

Where:

$EAUC$ is the equivalent annual uniform cost

NPW is the total net present worth of the strategy over the analysis period

i is the discount rate

N is the analysis period (50 years)

The incremental costs of EAUC are calculated similarly to the incremental costs for the present worth. First, all the equivalent annual costs are converted to an annual Present Worth cost, and then each annual present worth cost is added to the previous annual present worth cost. The analysis is performed on assumed cost data for treatments based on engineering experience and some historical data from municipalities in Ontario. Relative relation among different cost items was taken into consideration for treatments cost estimates. The objective of using cost data is to compare different strategies rather than provide the exact value for future expenditures.

The discount rate reflects the true time value of money. It describes the opportunity value of the money, such that money being spent now is more valuable than that being spent in the future, since today's spending could be invested in other projects, which could yield a return. Discount rates can significantly affect the analysis results; therefore, reasonable discount rates that reflect historical trends over longer periods of time should be used. For public sector projects, a discount rate of 3% to 5% has typically been used for economic analysis. For this study, a discount rate of 4% is used, though this value can be changed as needed within the developed tool as will be shown later and updated cost will be generated automatically.

6.4.2 Costs

The M&R activity unit costs are described in Table 6-1. These estimated costs are based on data collected from different transportation agencies in Southern Ontario. These costs represent the agencies' costs only, and do not include any user costs such as the user delay costs, vehicle operating costs, etc. The analysis presented herein has the objective of developing a sustainability plan for different rehabilitation alternatives both after they are implemented and throughout their service life. Therefore, the salvage values are not considered in comparing competing M&R strategies between models. Alt1 to Alt9, shown in the cost table, are additional alternatives coded in the decision support tool discussed later, which is used to facilitate the addition of new rehabilitation alternatives based on user choice.

6.4.3 Geometry

It was assumed that the roadway geometry, including the number of lanes, would not change during the analysis period (minimum 50 years), since this would result in new construction.

6.4.4 Maintenance and Rehabilitation Activities

Different types of rehabilitation activities are typically considered in the LCCA. These activities can be generally classified into the following categories:

- Preventive Maintenance Activities
- Light Rehabilitation Activities
- Heavy Rehabilitation Activities
- Construction/Reconstruction
- Localized Repair

Table 6-1: Unit Costs used in LCCA

Treatment	Description	Unit Cost ($\$/m^2$)
Fog Seal	Sealant application to prevent weathering and raveling	**2.50**
Crk Seal	Routing and Sealing of crack	**5.00**
Mill 80 mm + 80 mm AC O/L	Mill 80 mm AC and Overlay 80 mm of AC	**28.10**
100 mm AC O/L	Asphalt Concrete Overlay of 100 mm	**25.10**
Crk Seal (10% cracking)	Assumes 10% of the surface requires crack sealing	**0.50**
Crk Seal (15% cracking)	Assumes 15% of the surface requires crack sealing	**0.75**
Crk Seal (20% cracking)	Assumes 20% of the surface requires crack sealing	**1.00**
Earth removal	Remove 300 mm of earth	**19.50**
Mill 50 mm + 50 mm AC O/L	Mill 50 mm AC and Overlay 50 mm of AC	**18.85**
Pulverize	Asphalt Pulverization	**6.00**
Pulv + 100 mm AC O/L	Pulverize & Pave -– Recon	**31.10**
Microsurfacing	Microsurfacing	**3.30**
50 mm AC O/L	Asphalt Concrete Overlay of 50 mm	**12.55**
Full Recon - Local	Full Reconstruction (AC or COM) for Arterials	**100.00**
Cold-in-Place Recycling	Cold-in-Place Recycling	**31.00**
Strip & AC Overlay	Strip All AC	**49.00**
Full Recon - Arterial	Full Reconstruction for Arterials	**194.10**
Full Recon - Collector	Full Reconstruction for Collectors	**170.60**
80 mm AC O/L	Asphalt Concrete Overlay of 50 mm	**20.00**
Alt1	Alt1	
Alt2	Alt2	
Alt3	Alt3	
Alt4	Alt4	
Alt5	Alt5	
Alt6	Alt6	
Alt7	Alt7	
Alt8	Alt8	
Alt9	Alt9	

Preventive maintenance activities are planned activities implemented when the pavement is in the excellent to good condition, in order to improve pavement safety or functional conditions and/or slow the rate of pavement deterioration. The main purpose of these activities is to reduce the water and air infiltration into the pavement structure, slowing the stripping and oxidization process of the asphalt and therefore reducing the rate of deterioration of the pavement. These preventive maintenance activities include crack sealing, surface treatments, and micro surfacing. It should be noted that preventive maintenance is different from corrective maintenance, which is typically implemented as a stopgap measure, holding the condition of a pavement section until a rehabilitation activity can be implemented. Figure 6-1 shows a typical performance model for a pavement section and the impact of preventive maintenance on the pavement performance. As shown in the figure, preventive maintenance can either improve the pavement condition or reduce the rate of deterioration. In all cases, preventive maintenance can enhance pavement performance and reduce the life-cycle costs of highway facilities. Light rehabilitation activities are implemented when the pavement condition is relatively fair, where functional improvement might be needed.

While light rehabilitation activities improve the functional performance and safety of the pavement surface, their impact on the structural condition of the pavement is minimal. Examples of these activities include mill, overlay and thin overlays activities. Heavy rehabilitation activities are needed to improve the structural condition of the pavement by either adding significant thickness or replacing a significant portion of the pavement structure. These activities include thick overlays, and AC partial reconstruction. Localized repairs are reserved for distressed or failed areas. They are typically reactive activities based on inspection data. They include patching, deep patching and localized reconstruction due to unaddressed drainage problems. Table 6-2 shows the list of rehabilitation maintenance and activities considered in this decision-making framework and model comparison, with associated costs presented in Table 6-1.

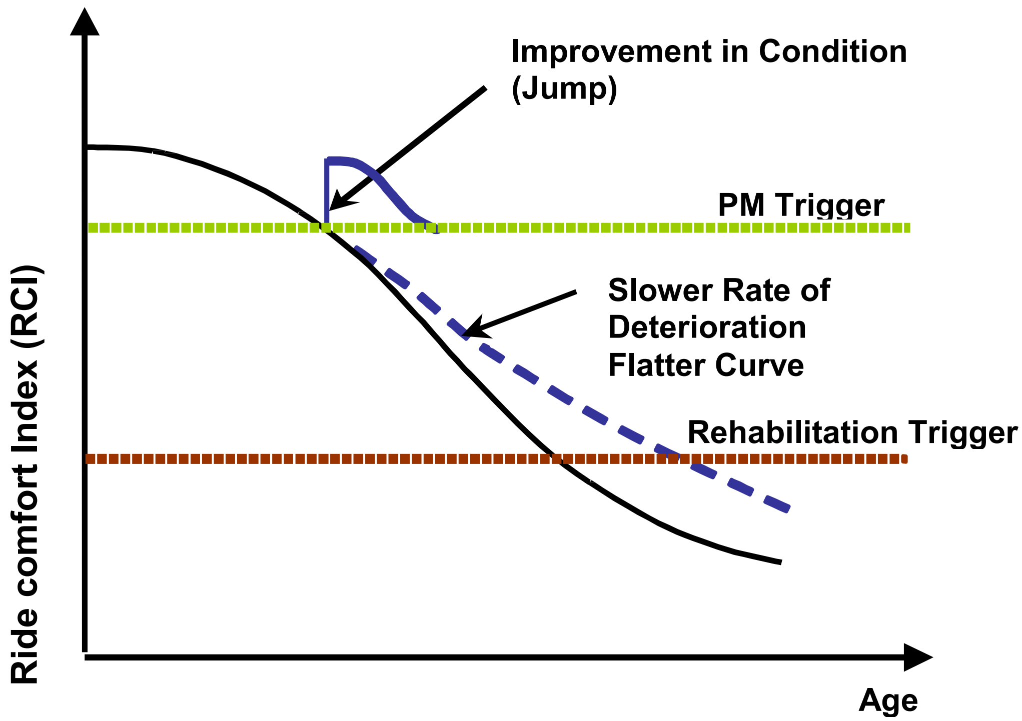


Figure 6-1: Impact of Preventive Maintenance Activities on Pavement Performance (Hein and Croteau 2004)

Table 6-2: List of Rehabilitation Activities

Activity Code	Activity Description
1	Full Reconstruction AC (Arterial)
2	Mill 80 & overlay 80
3	Full Reconstruction AC (Collector)
4	Strip & AC Overlay
5	Cold-in-Place Recycling
6	Pulverize & AC Overlay
7	Full Reconstruction AC (Local)
8	Overlay AC 50 mm
9	Overlay AC 80 mm
10	Overlay AC100 mm
11	Mill 50 & overlay 50
12	*(Blank for a adding new activity)*
13	*(Blank for a adding new activity)*

6.4.5 Maintenance and Rehabilitation (M&R) Strategies

In general, there are two strategies that can be considered for the sustainability plan included in the decision-making framework. The first strategy is to consider only pavement rehabilitation activities, such that the pavement is allowed to deteriorate until it reaches the end of its service life of its next construction or major rehabilitation activity, and then another reconstruction or major rehabilitation is implemented. The second strategy is to include surface treatments or preventive maintenance activities to extend the service life of the pavement. The decision-making framework developed has the flexibility to include either of the two strategies based on user selection; however, only single light or heavy rehabilitation activities are presented in this study at trigger conditions to demonstrate the difference between the models. No localized repair or preventive maintenance activates are therefore used at any time in the pavement's life to isolate variation incurred in cost due to rehabilitation change and only the one strategy is included in the comparison.

6.4.6 Section Selected for Analysis

To illustrate the difference between the impacts of the models used in the analysis, a section with a length of 1.4 km and a 3.5 m lane width is used to calculate the quantities needed for different rehabilitations alternatives.

6.5 DECISION-MAKING CONDITIONS

Classified in a similar fashion to the design of experiment (DOE) previously described in Chapter 3, there are 54 conditions resulting from the combination of two subgrade condition types, three thickness categories, three traffic levels, and three functional classes, as shown in Figure 6-2. Each condition combination in the decision matrix represents a unique condition and has been assigned with possible treatment options from the treatment list in Table 6-3. It should be noted that more than one rehabilitation alternative could be applicable to the same condition or same rehabilitation alternative for more than one condition-based user decision. Table 6-3 illustrates the rehabilitation activities assigned to each condition for model impact comparison. The numbers shown in each cell represent the code of possible activities for each condition, as defined in Table 6-2. The criteria used to classify traffic pattern, subgrade condition and thickness threshold levels are similar to the one explained in section 3.7 in Table 3-4 and Table 3-5.

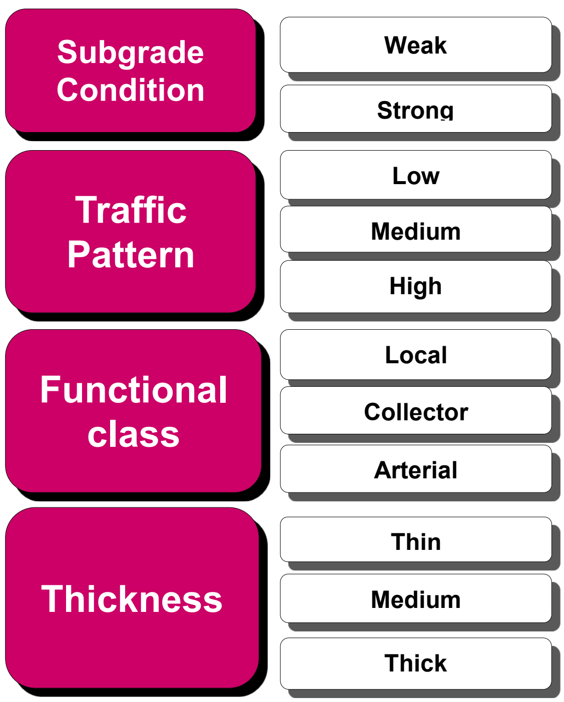


Figure 6-2: Decision-making Factors

Table 6-3: Rehabilitation Activities Assigned for Each Condition

Subgrade	Functional class	Traffic	Thickness		
			Thin	**Medium**	**Thick**
Weak	**Local**	**Low**	2,4	2,5	5,6
		Medium	7,2	7,4	7,5
		High	7,4	7,5	7,6
	Collector	**Low**	2,4	4,5	5,6
		Medium	3,2	3,4	3,5
		High	3,4	3,5	3,6
	Arterial	**Low**	2,4	4,5	5,6
		Medium	1,2	1,4	1,5
		High	1,4	1,5	1,6
Strong	**Local**	**Low**	8,4	8,5	8,6
		Medium	9,2	9,4	9,5
		High	10,4	10,5	10,6
	Collector	**Low**	9,4	9,5	9,6
		Medium	10,2	10,4	10,5
		High	11,4	11,5	11,6
	Arterial	**Low**	10,4	10,5	10,6
		Medium	11,2	11,4	11,5
		High	2,4	2,5	2,6

6.6 SUMMARY

This Chapter provided comprehensive details about the economic principles used in the development of decision-making framework for rehabilitation selection. The next Chapter will describe in details the implementation of an automated decision-making tool that to incorporate the decision framework discussed herein.

7.0 Development of M-E Model Based Decision-making Tool for Rehabilitation Alternative Selection

7.1 DECISION-MAKING MECHANISM

The decision-making framework and economic principles presented in previous Chapter are used to develop an automated decision-making tool for the alternatives selection. Figure 7-1 illustrates the procedures used to develop the tool. The first step is to prepare site-specific data such as project geometric data (length and width) and discount rate, followed by classifying the road under consideration based on the four DOE conditions and identifying the rehabilitation alternative set applicable to each condition. The next step is to carry out a comprehensive life cycle cost analysis (LCCA) for each strategy. Two concurrent LCCAs are performed simultaneously for each alternative. In the first LCCA scenario, the pavement deteriorates using a traditional empirical model. In the second LCCA, pavement deteriorates according to the newly developed M-E model. Once the LCCA is executed over a 50-year period, a comparison among possible strategies is presented graphically with possible rehabilitation actions.

Figure 7-1 shows the interface of the developed decision-making tool. It illustrates how the decision framework procedures are implemented into the decision support tool. By selecting different factor combinations in the inputs section, a new condition is identified and rehabilitation alternatives associated with the selected condition are populated accordingly in the rehabilitation option box. The tool will calculate the project area based on site-specific geometric data entered in section inputs, which will automatically update alternatives in the LCCA. Two sets of incremental equivalent annual uniform costs (EAUC) are displayed graphically for each rehabilitation alternative. The first incremental EAUC considers pavement deterioration using traditional empirical models, while the other incremental EAUC accounts for pavement deterioration following M-E models. The pavement is assumed to return to 100% RCI after the implementation of the rehabilitation activity. RCI deterioration over the analysis period is displayed graphically for each model. In addition, the net present worth cost is displayed for each alternative considered for each model type.

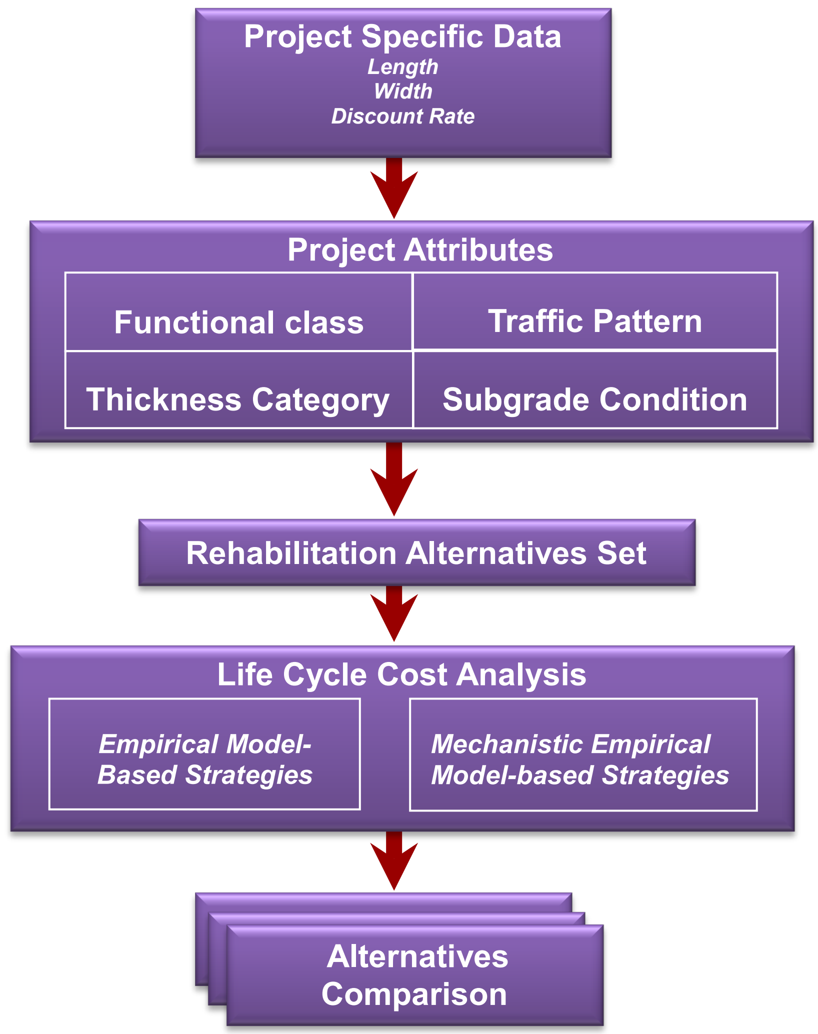


Figure 7-1: Schematic Decision Framework for Alternatives Selection

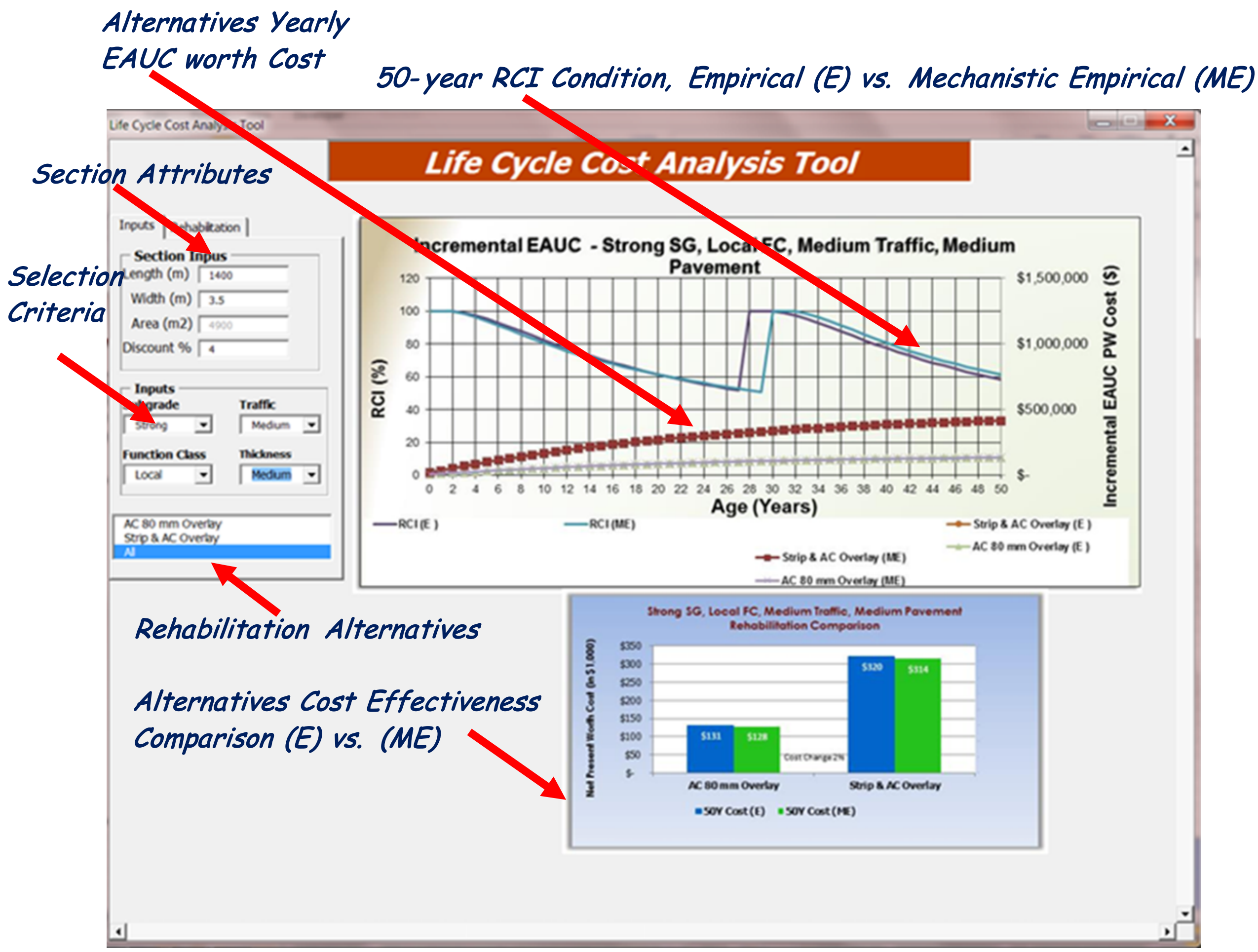


Figure 7-2: Decision-making LCCA Tool Interface

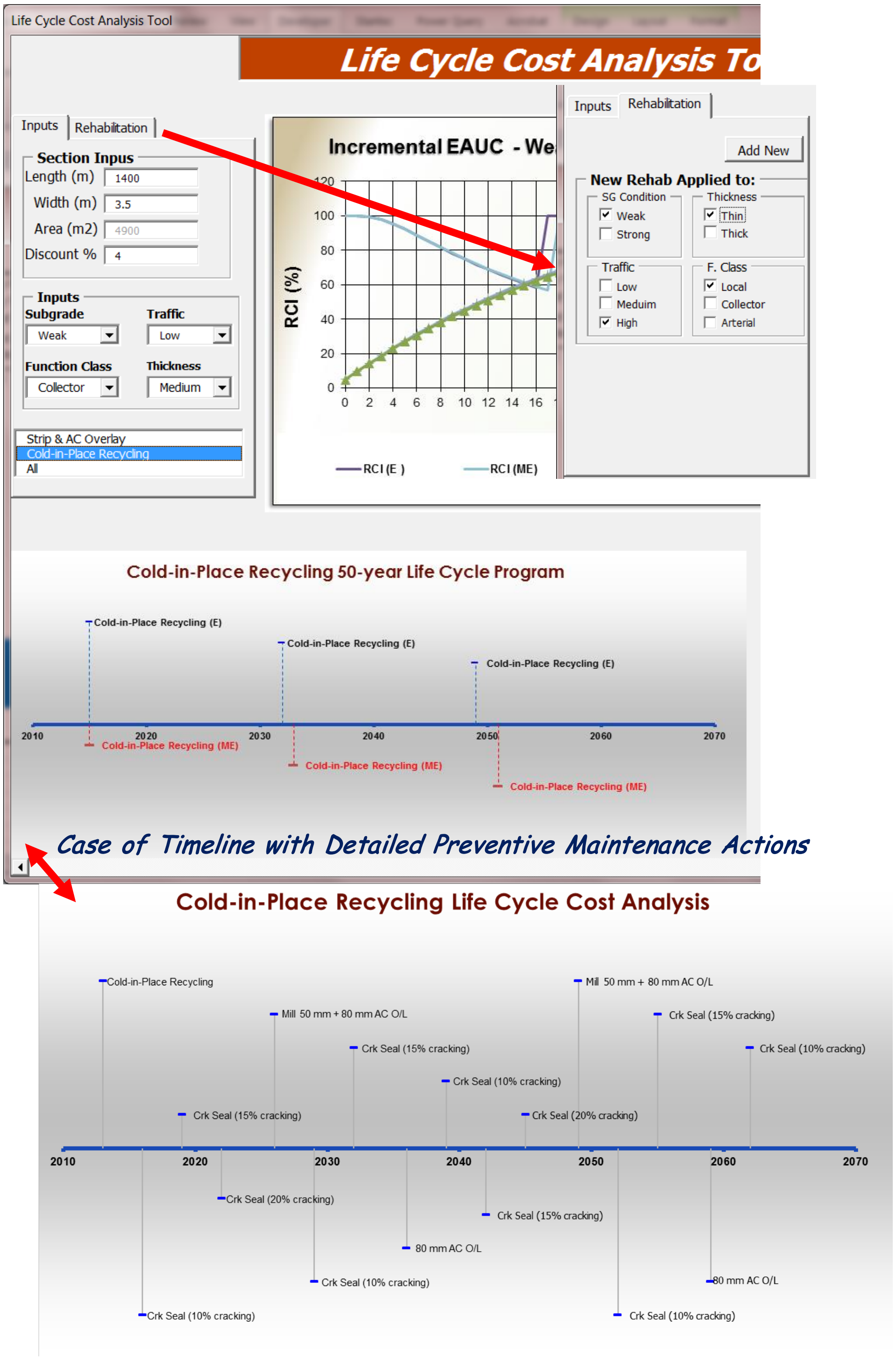


Figure 7-3: Timeline Actions along Analysis Period

7.2 DECISION-MAKING TOOL CAPABILITIES

7.2.1 Detailed Periodic Timeline Actions

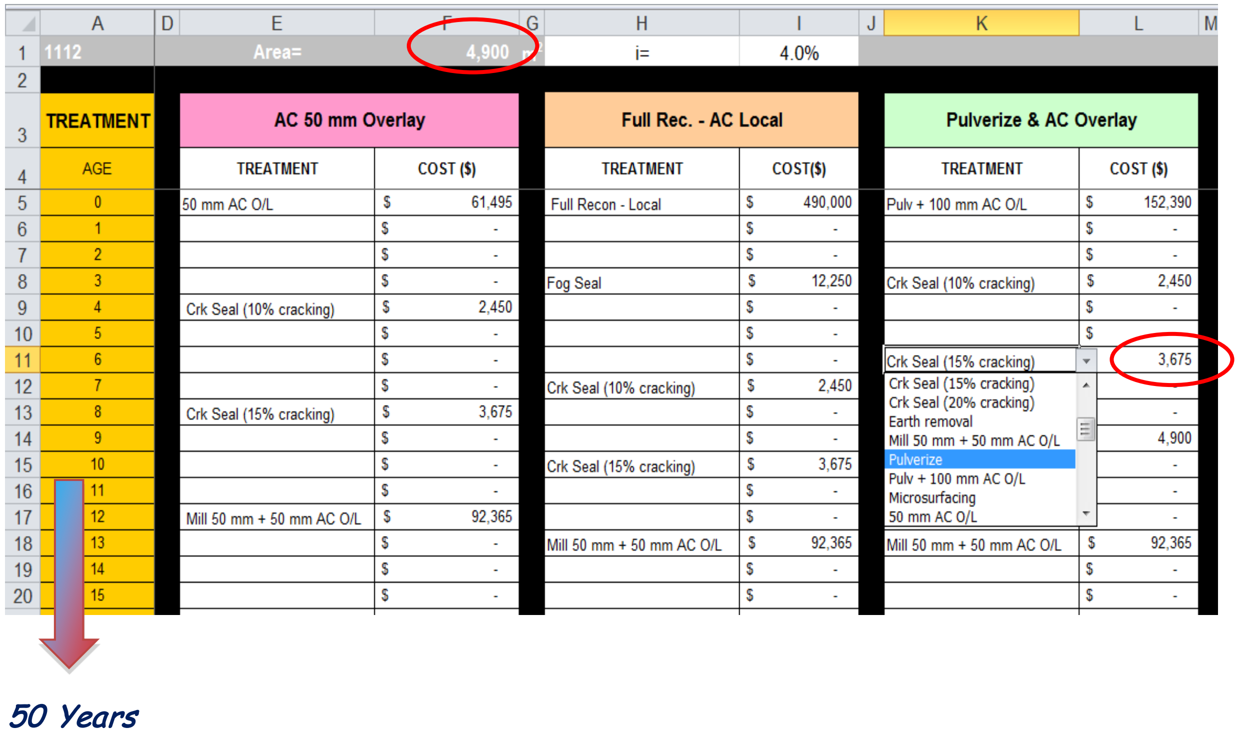
Selecting individual alternatives from the alternative options box will display the activity timeline over the analysis period, as shown in Figure 7-3. This will help plan in advance for the next action, especially when the strategy includes several preventive maintenance actions (which are not used in this scenario).

7.2.2 Adding New Rehabilitation Alternative

The rehabilitation tab shown in Figure 7-3 provides the capability to add additional rehabilitation alternatives to any specific condition. Once a new alternative is added, the underlying decision matrix presented previously in Table 6-3 is updated to reflect these changes, along with associated cost.

7.2.3 Interactive strategy Actions Update

The tool has the flexibility to change yearly actions based on user selection to reflect the best set of preventive maintenance activities and/or major rehabilitation, as shown in Figure 7-4. If activity is changed at any time of the analysis period, the associated cost is updated automatically based on selected unit cost activity.



	A	E	F	H	I	K	L
1	1112	Area=	4,900 m²	i=	4.0%		
3	TREATMENT	AC 50 mm Overlay		Full Rec. - AC Local		Pulverize & AC Overlay	
4	AGE	TREATMENT	COST ($)	TREATMENT	COST($)	TREATMENT	COST ($)
5	0	50 mm AC O/L	$ 61,495	Full Recon - Local	$ 490,000	Pulv + 100 mm AC O/L	$ 152,390
6	1		$ -		$ -		$ -
7	2		$ -		$ -		$ -
8	3		$ -	Fog Seal	$ 12,250	Crk Seal (10% cracking)	$ 2,450
9	4	Crk Seal (10% cracking)	$ 2,450		$ -		$ -
10	5		$ -		$ -		$
11	6		$ -		$ -	Crk Seal (15% cracking)	3,675
12	7		$ -	Crk Seal (10% cracking)	$ 2,450		
13	8	Crk Seal (15% cracking)	$ 3,675		$ -		-
14	9		$ -		$ -		4,900
15	10		$ -	Crk Seal (15% cracking)	$ 3,675		-
16	11		$ -		$ -		-
17	12	Mill 50 mm + 50 mm AC O/L	$ 92,365		$ -		-
18	13		$ -	Mill 50 mm + 50 mm AC O/L	$ 92,365	Mill 50 mm + 50 mm AC O/L	$ 92,365
19	14		$ -		$ -		$ -
20	15		$ -		$ -		$ -

Figure 7-4: Interactive LCCA Activity Selection

7.3 LCCA CASE STUDY

Figure 7-5 and Figure 7-6 show an example of detailed cost calculation for a 50mm overlay strategy. All alternatives listed previously in Table 6-2 are embedded in the tool along with their associated costs. These figures illustrate how the change from empirical models to M-E models impacted the year when the next rehabilitation was implemented and the corresponding overall LCCA of the alternative.

TREATMENT	50 mm AC O/L			Empirical Model LCCA						
AGE	TREATMENT	COST($)	RCI (E)	TREATMENT	COST($)	PW	Inc_PW	EAUC_yr	EAUC_PW	ln_EAUC_PW
0	50 mm AC O/L	$ 61,495	100.0	50 mm AC O/L	$ 61,495	$ 61,495	$ 61,495	$ 4,670	$ 4,670	$ 4,670
1		$ -	100.0		$ -	$ -	$ 61,495	$ 4,670	$ 4,490	$ 9,161
2		$ -	99.6		$ -	$ -	$ 61,495	$ 4,670	$ 4,318	$ 13,478
3		$ -	98.2		$ -	$ -	$ 61,495	$ 4,670	$ 4,152	$ 17,630
4		$ -	95.9		$ -	$ -	$ 61,495	$ 4,670	$ 3,992	$ 21,622
5		$ -	92.9		$ -	$ -	$ 61,495	$ 4,670	$ 3,838	$ 25,460
6		$ -	89.6		$ -	$ -	$ 61,495	$ 4,670	$ 3,691	$ 29,151
7		$ -	86.2		$ -	$ -	$ 61,495	$ 4,670	$ 3,549	$ 32,700
8		$ -	82.9		$ -	$ -	$ 61,495	$ 4,670	$ 3,412	$ 36,113
9		$ -	79.6		$ -	$ -	$ 61,495	$ 4,670	$ 3,281	$ 39,394
10		$ -	76.5		$ -	$ -	$ 61,495	$ 4,670	$ 3,155	$ 42,549
11		$ -	73.5		$ -	$ -	$ 61,495	$ 4,670	$ 3,034	$ 45,582
12		$ -	70.7		$ -	$ -	$ 61,495	$ 4,670	$ 2,917	$ 48,499
13		$ -	68.0		$ -	$ -	$ 61,495	$ 4,670	$ 2,805	$ 51,304
14		$ -	65.5		$ -	$ -	$ 61,495	$ 4,670	$ 2,697	$ 54,001
15		$ -	63.1		$ -	$ -	$ 61,495	$ 4,670	$ 2,593	$ 56,594
16		$ -	60.8		$ -	$ -	$ 61,495	$ 4,670	$ 2,493	$ 59,087
17		$ -	58.7		$ -	$ -	$ 61,495	$ 4,670	$ 2,397	$ 61,485
18		$ -	56.6		$ -	$ -	$ 61,495	$ 4,670	$ 2,305	$ 63,790
19		$ -	54.7		$ -	$ -	$ 61,495	$ 4,670	$ 2,217	$ 66,007
20		$ -	52.9		$ -	$ -	$ 61,495	$ 4,670	$ 2,131	$ 68,138
21	50 mm AC O/L	$ 61,495	51.1	50 mm AC O/L	$ 61,495	$ 26,986	$ 88,481	$ 4,670	$ 2,049	$ 70,187
22		$ -	100.0		$ -	$ -	$ 88,481	$ 4,670	$ 1,971	$ 72,158
23		$ -	100.0		$ -	$ -	$ 88,481	$ 4,670	$ 1,895	$ 74,053
24		$ -	99.6		$ -	$ -	$ 88,481	$ 4,670	$ 1,822	$ 75,875
25		$ -	98.2		$ -	$ -	$ 88,481	$ 4,670	$ 1,752	$ 77,626
26		$ -	95.9		$ -	$ -	$ 88,481	$ 4,670	$ 1,684	$ 79,311
27		$ -	92.9		$ -	$ -	$ 88,481	$ 4,670	$ 1,620	$ 80,931
28		$ -	89.6		$ -	$ -	$ 88,481	$ 4,670	$ 1,557	$ 82,488
29		$ -	86.2		$ -	$ -	$ 88,481	$ 4,670	$ 1,497	$ 83,985
30		$ -	82.9		$ -	$ -	$ 88,481	$ 4,670	$ 1,440	$ 85,425
31		$ -	79.6		$ -	$ -	$ 88,481	$ 4,670	$ 1,384	$ 86,810
32		$ -	76.5		$ -	$ -	$ 88,481	$ 4,670	$ 1,331	$ 88,141
33		$ -	73.5		$ -	$ -	$ 88,481	$ 4,670	$ 1,280	$ 89,421
34		$ -	70.7		$ -	$ -	$ 88,481	$ 4,670	$ 1,231	$ 90,652
35		$ -	68.0		$ -	$ -	$ 88,481	$ 4,670	$ 1,183	$ 91,835
36		$ -	65.5		$ -	$ -	$ 88,481	$ 4,670	$ 1,138	$ 92,973
37		$ -	63.1		$ -	$ -	$ 88,481	$ 4,670	$ 1,094	$ 94,067
38		$ -	60.8		$ -	$ -	$ 88,481	$ 4,670	$ 1,052	$ 95,120
39		$ -	58.7		$ -	$ -	$ 88,481	$ 4,670	$ 1,012	$ 96,131
40		$ -	56.6		$ -	$ -	$ 88,481	$ 4,670	$ 973	$ 97,104
41		$ -	54.7		$ -	$ -	$ 88,481	$ 4,670	$ 935	$ 98,039
42	50 mm AC O/L	$ 61,495	52.9	50 mm AC O/L	$ 61,495	$ 11,842	$100,323	$ 4,670	$ 899	$ 98,939
43		$ -	51.1		$ -	$ -	$100,323	$ 4,670	$ 865	$ 99,803
44		$ -	100.0		$ -	$ -	$100,323	$ 4,670	$ 831	$ 100,635
45		$ -	100.0		$ -	$ -	$100,323	$ 4,670	$ 800	$ 101,434
46		$ -	99.6		$ -	$ -	$100,323	$ 4,670	$ 769	$ 102,203
47		$ -	98.2		$ -	$ -	$100,323	$ 4,670	$ 739	$ 102,942
48		$ -	95.9		$ -	$ -	$100,323	$ 4,670	$ 711	$ 103,653
49		$ -	92.9		$ -	$ -	$100,323	$ 4,670	$ 683	$ 104,336
50		$ -	89.6		$ -	$ -	$100,323	$ 4,670	$ 657	$ 104,994
Project Totals ($)		$ 184,485		$ 100,323	$ 184,485	$ 100,323	$100,323	$ 4,670	$ 104,994	$ 104,994

Figure 7-5: Detailed Calculation for Empirical-Model Based LCCA Alternative

TREATMENT	50 mm AC O/L			Mechanistic Empirical Model LCCA						
AGE	TREATMENT	COST ($)	RCI (ME)	TREATMENT	COST($)	PW	Inc_PW	EAUC_yr	EAUC_PW	In_EAUC_PW
0	50 mm AC O/L	$ 61,495	100.0	50 mm AC O/L	$ 61,495	$ 61,495	$ 61,495	$ 3,647	$ 3,647	$ 3,647
1		$ -	100.0		$ -	$ -	$ 61,495	$ 3,647	$ 3,507	$ 7,154
2		$ -	99.7		$ -	$ -	$ 61,495	$ 3,647	$ 3,372	$ 10,526
3		$ -	98.6		$ -	$ -	$ 61,495	$ 3,647	$ 3,242	$ 13,769
4		$ -	96.7		$ -	$ -	$ 61,495	$ 3,647	$ 3,118	$ 16,886
5		$ -	94.3		$ -	$ -	$ 61,495	$ 3,647	$ 2,998	$ 19,884
6		$ -	91.8		$ -	$ -	$ 61,495	$ 3,647	$ 2,882	$ 22,766
7		$ -	89.1		$ -	$ -	$ 61,495	$ 3,647	$ 2,772	$ 25,538
8		$ -	86.5		$ -	$ -	$ 61,495	$ 3,647	$ 2,665	$ 28,203
9		$ -	83.9		$ -	$ -	$ 61,495	$ 3,647	$ 2,562	$ 30,766
10		$ -	81.5		$ -	$ -	$ 61,495	$ 3,647	$ 2,464	$ 33,230
11		$ -	79.2		$ -	$ -	$ 61,495	$ 3,647	$ 2,369	$ 35,599
12		$ -	77.0		$ -	$ -	$ 61,495	$ 3,647	$ 2,278	$ 37,877
13		$ -	74.9		$ -	$ -	$ 61,495	$ 3,647	$ 2,190	$ 40,067
14		$ -	73.0		$ -	$ -	$ 61,495	$ 3,647	$ 2,106	$ 42,173
15		$ -	71.1		$ -	$ -	$ 61,495	$ 3,647	$ 2,025	$ 44,199
16		$ -	69.4		$ -	$ -	$ 61,495	$ 3,647	$ 1,947	$ 46,146
17		$ -	67.7		$ -	$ -	$ 61,495	$ 3,647	$ 1,872	$ 48,018
18		$ -	66.2		$ -	$ -	$ 61,495	$ 3,647	$ 1,800	$ 49,819
19		$ -	64.7		$ -	$ -	$ 61,495	$ 3,647	$ 1,731	$ 51,550
20		$ -	63.3		$ -	$ -	$ 61,495	$ 3,647	$ 1,665	$ 53,214
21		$ -	61.9		$ -	$ -	$ 61,495	$ 3,647	$ 1,601	$ 54,815
22		$ -	60.7		$ -	$ -	$ 61,495	$ 3,647	$ 1,539	$ 56,354
23		$ -	59.5		$ -	$ -	$ 61,495	$ 3,647	$ 1,480	$ 57,834
24		$ -	58.3		$ -	$ -	$ 61,495	$ 3,647	$ 1,423	$ 59,256
25		$ -	57.2		$ -	$ -	$ 61,495	$ 3,647	$ 1,368	$ 60,625
26		$ -	56.2		$ -	$ -	$ 61,495	$ 3,647	$ 1,316	$ 61,940
27		$ -	55.2		$ -	$ -	$ 61,495	$ 3,647	$ 1,265	$ 63,205
28		$ -	54.2		$ -	$ -	$ 61,495	$ 3,647	$ 1,216	$ 64,421
29		$ -	53.3		$ -	$ -	$ 61,495	$ 3,647	$ 1,169	$ 65,591
30		$ -	52.5		$ -	$ -	$ 61,495	$ 3,647	$ 1,125	$ 66,715
31		$ -	51.6		$ -	$ -	$ 61,495	$ 3,647	$ 1,081	$ 67,796
32		$ -	50.8		$ -	$ -	$ 61,495	$ 3,647	$ 1,040	$ 68,836
33	50 mm AC O/L	$ 61,495	100.0	50 mm AC O/L	$ 61,495	$ 16,855	$ 78,350	$ 3,647	$ 1,000	$ 69,836
34		$ -	100.0		$ -	$ -	$ 78,350	$ 3,647	$ 961	$ 70,797
35		$ -	99.7		$ -	$ -	$ 78,350	$ 3,647	$ 924	$ 71,721
36		$ -	98.6		$ -	$ -	$ 78,350	$ 3,647	$ 889	$ 72,610
37		$ -	96.7		$ -	$ -	$ 78,350	$ 3,647	$ 855	$ 73,465
38		$ -	94.3		$ -	$ -	$ 78,350	$ 3,647	$ 822	$ 74,286
39		$ -	91.8		$ -	$ -	$ 78,350	$ 3,647	$ 790	$ 75,076
40		$ -	89.1		$ -	$ -	$ 78,350	$ 3,647	$ 760	$ 75,836
41		$ -	86.5		$ -	$ -	$ 78,350	$ 3,647	$ 730	$ 76,566
42		$ -	83.9		$ -	$ -	$ 78,350	$ 3,647	$ 702	$ 77,269
43		$ -	81.5		$ -	$ -	$ 78,350	$ 3,647	$ 675	$ 77,944
44		$ -	79.2		$ -	$ -	$ 78,350	$ 3,647	$ 649	$ 78,594
45		$ -	77.0		$ -	$ -	$ 78,350	$ 3,647	$ 624	$ 79,218
46		$ -	74.9		$ -	$ -	$ 78,350	$ 3,647	$ 600	$ 79,818
47		$ -	73.0		$ -	$ -	$ 78,350	$ 3,647	$ 577	$ 80,396
48		$ -	71.1		$ -	$ -	$ 78,350	$ 3,647	$ 555	$ 80,951
49		$ -	69.4		$ -	$ -	$ 78,350	$ 3,647	$ 534	$ 81,484
50		$ -	67.7		$ -	$ -	$ 78,350	$ 3,647	$ 513	$ 81,998
Project Totals ($)		$ 122,990		$ 78,350	$ 122,990	$ 78,350	$ 78,350	$ 3,647	$ 81,998	$ 81,998

Figure 7-6: Detailed Calculation for Mechanistic-Empirical Model Based LCCA Alternative

7.4 COMPARISON BETWEEN EMPIRICAL AND MECHANISTIC EMPIRICAL MODELS ON LCCA

As discussed previously in Chapter 3, the critical condition models are Models 3, 6, 8 and 13. These are the models that carry the most expected condition for each paramter. The following section discusses model comparisons for these conditions in more detail:

7.4.1 Model 3 Analysis Comparison Results

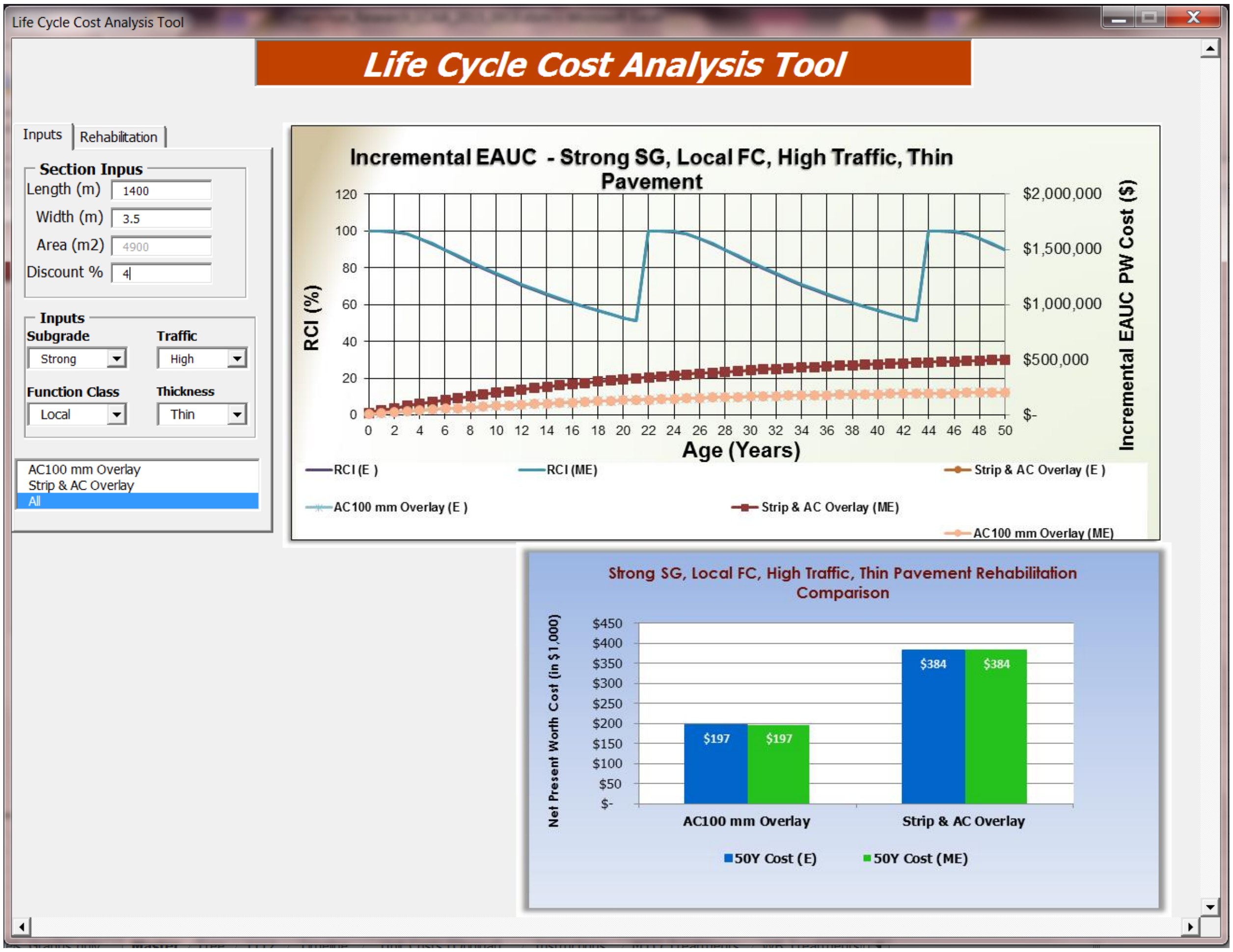


Figure 7-7: Model 3 Empirical vs. Mechanistic Empirical LCCA Results (Local Roads)

Model 3 represents pavement deterioration associated with strong subgrade, high traffic and thin pavement condition. Models were only developed for local roads. As seen in Figure 7-7, the developed M-E models were almost identical to the existing empirical models, producing an insignificant impact in cost estimates.

7.4.2 Model 6 Analysis Comparison Results

Models 6 represents pavement deterioration associated with weak subgrade, high traffic and thin pavement condition. The predicted service life for the empirical model was very close to the one predicted by M-E modeling; no significant impact was therefore noted in cost estimates. This was observed for the three functional classes, as shown in Figure 7-8, Figure 7-9 and Figure 7-10.

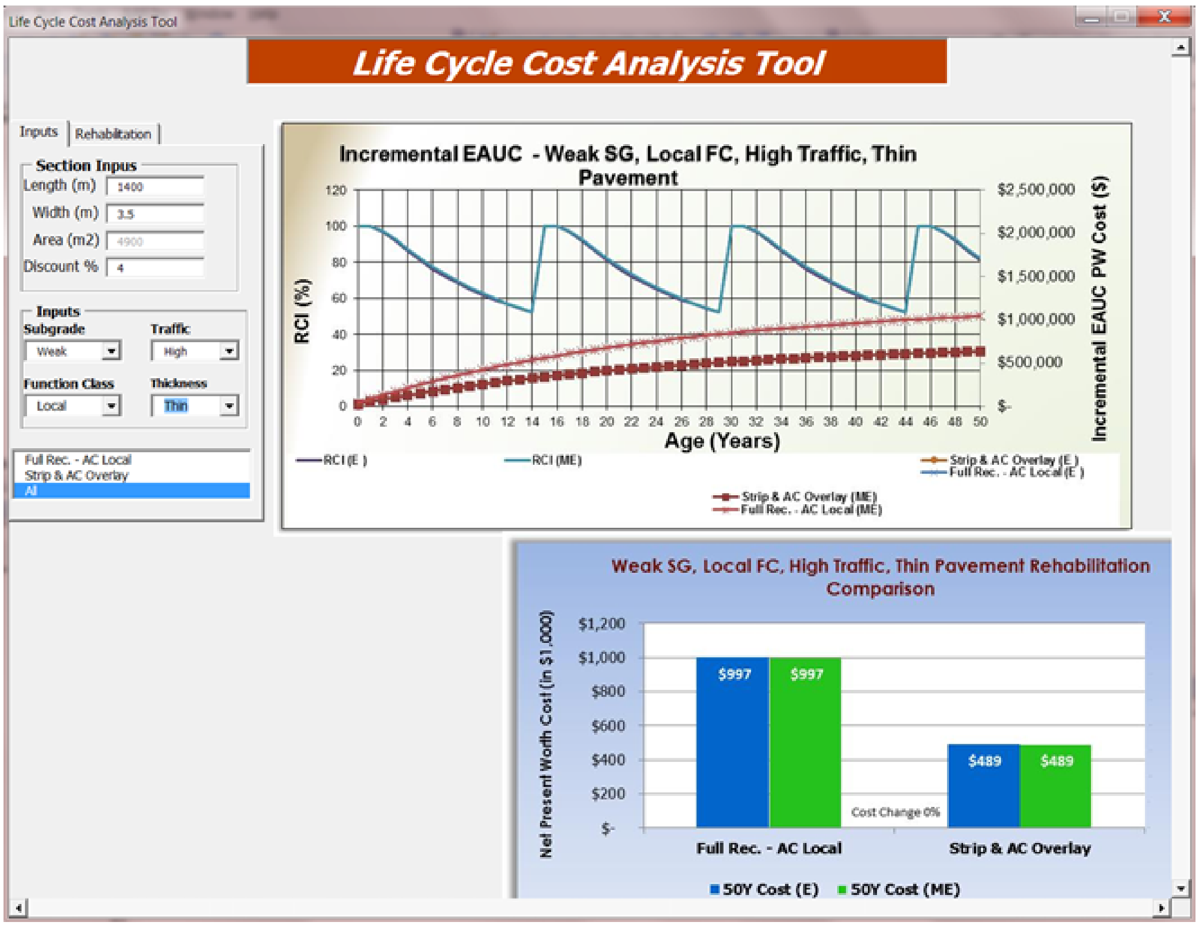


Figure 7-8: Model 6 Empirical vs Mechanistic Empirical LCCA Results (Local Roads)

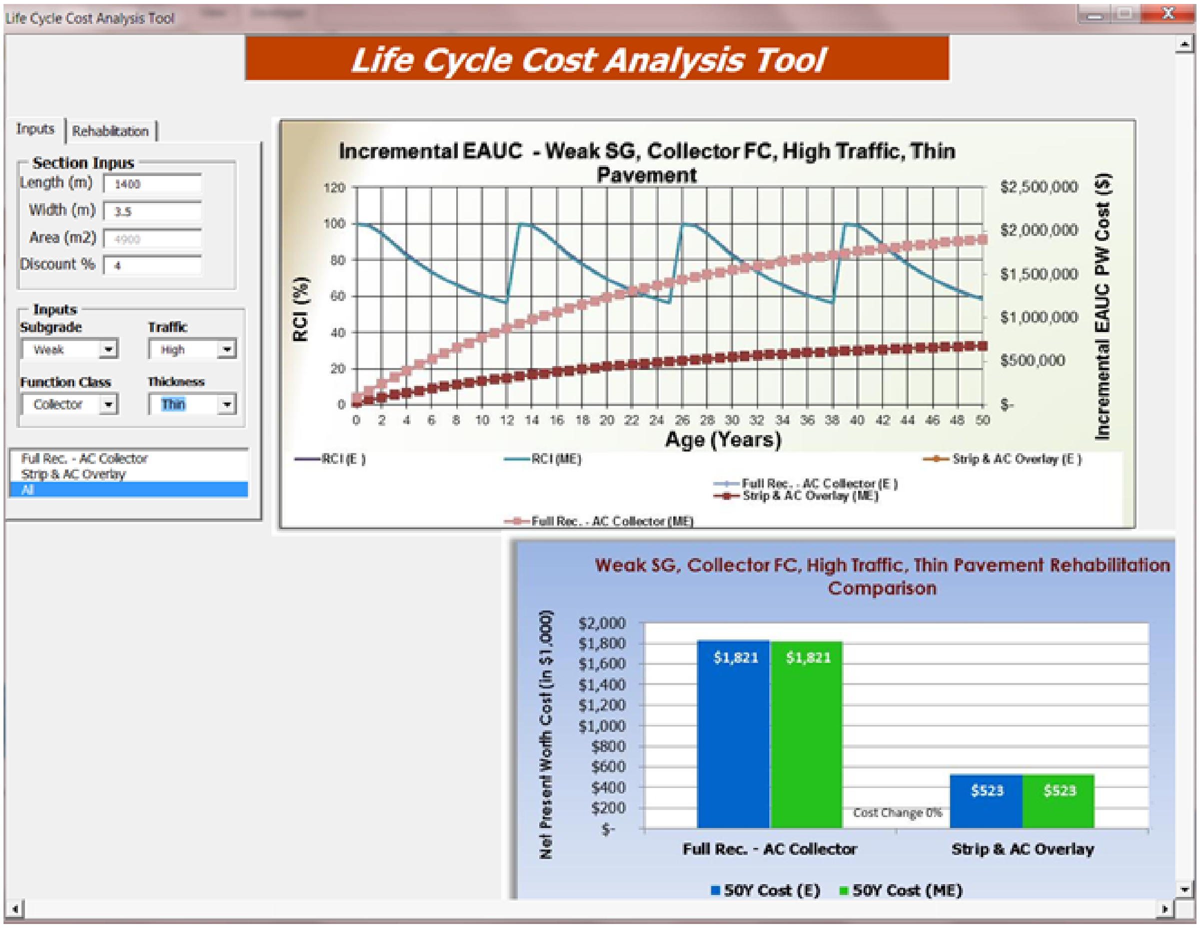


Figure 7-9: Model 6 Empirical vs Mechanistic Empirical LCCA Results (Collector Roads)

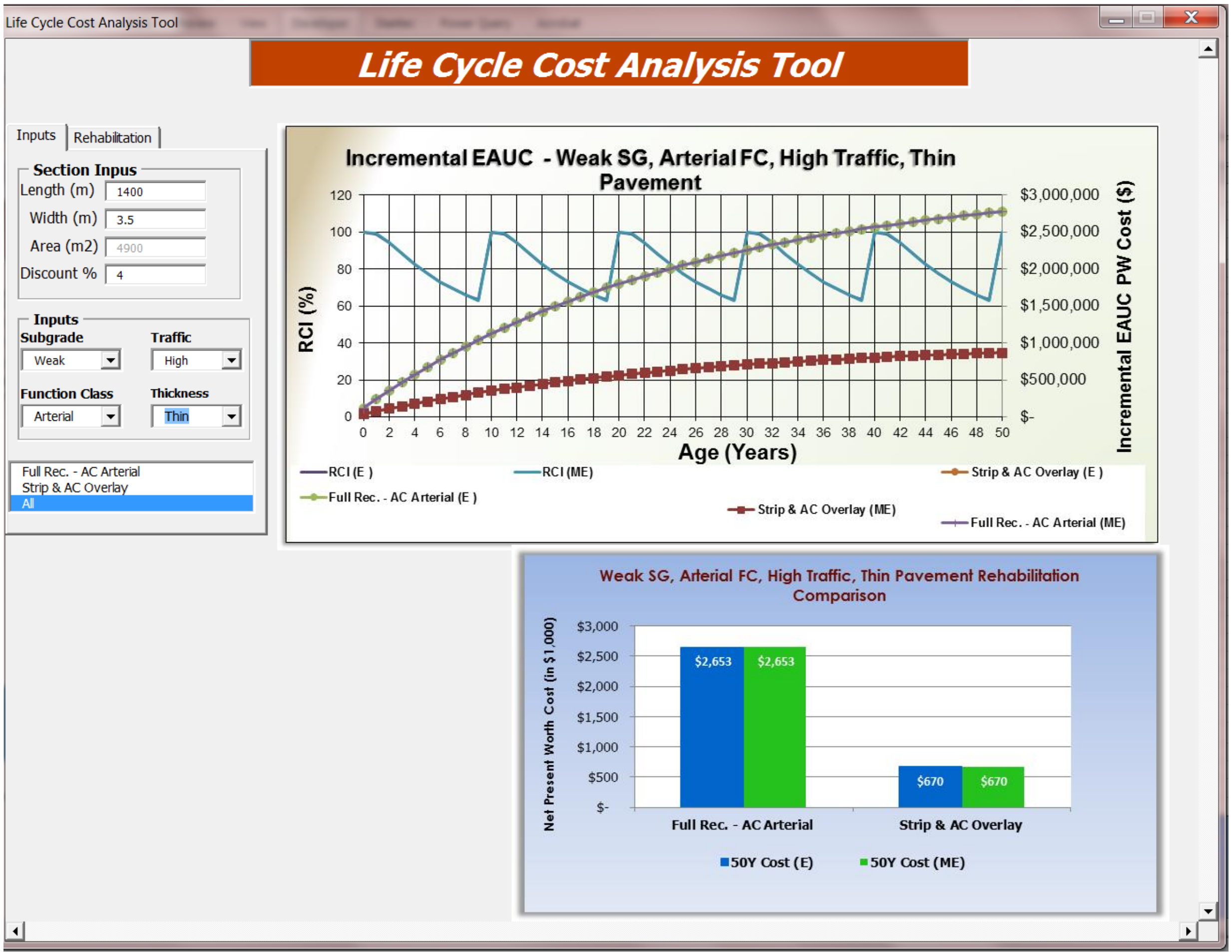


Figure 7-10: Model 6 Empirical vs Mechanistic Empirical LCCA Results (Arterial Roads)

7.4.3 Model 8 Analysis Comparison Results

Model 8 represents pavement deterioration associated with strong subgrade, medium traffic and medium thickness conditions. As can be seen from the RCI deterioration models for local functional classes, there is almost a two years difference between the trigger year for each model. This difference resulted in a 2% deference in cost estimate as shown in Figure 7-11.

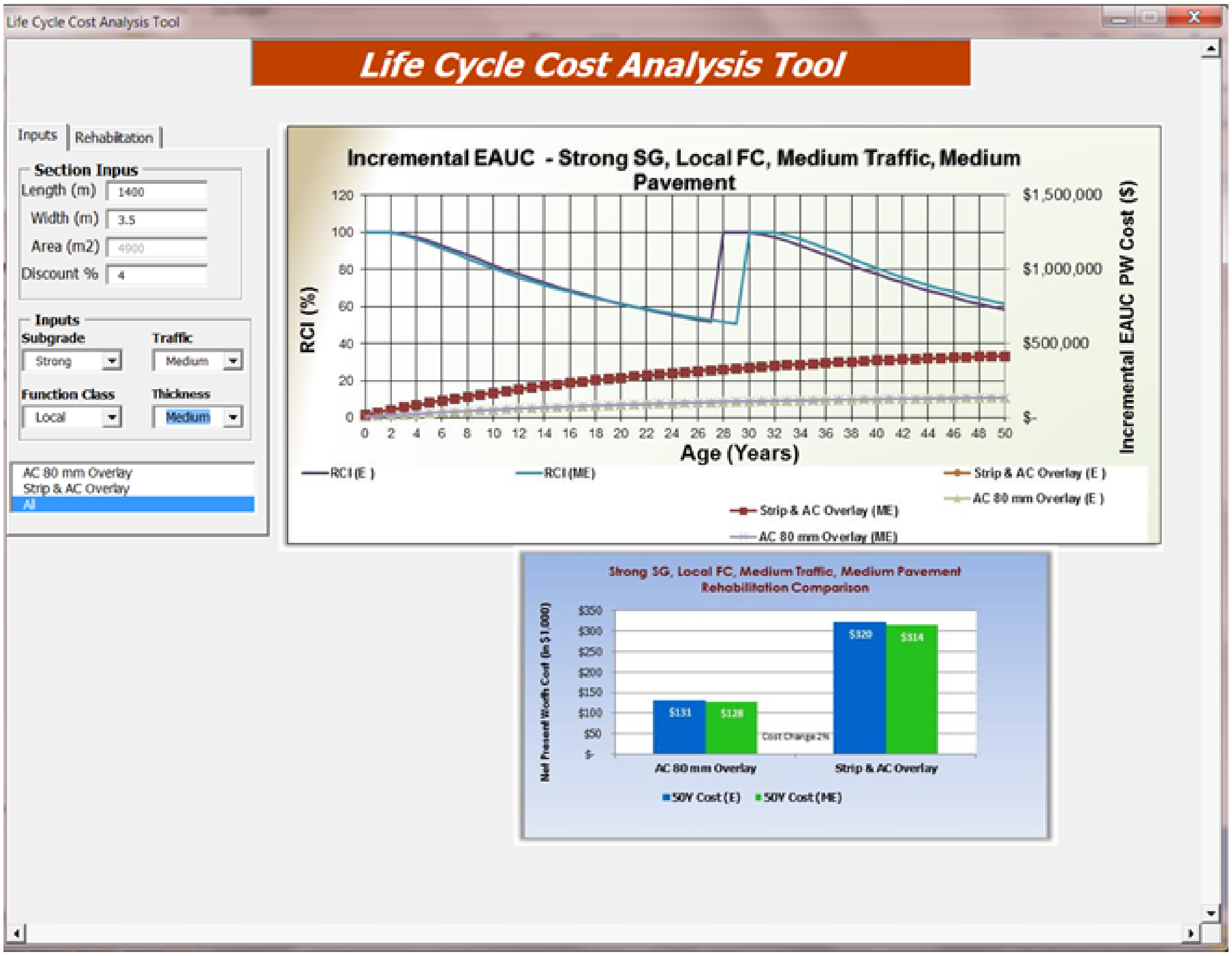


Figure 7-11: Model 8 Empirical vs Mechanistic Empirical LCCA Results (Local Roads)

For collector roads, empirical models deteriorated relatively quicker compared to local empirical models, with a 5 year difference; and much faster by 2 years compared to M-E local models. The empirical model tends to deteriorate with a higher rate compared to M-E models, which resulted in overestimating the cost by 4% difference as shown in Figure 7-12.

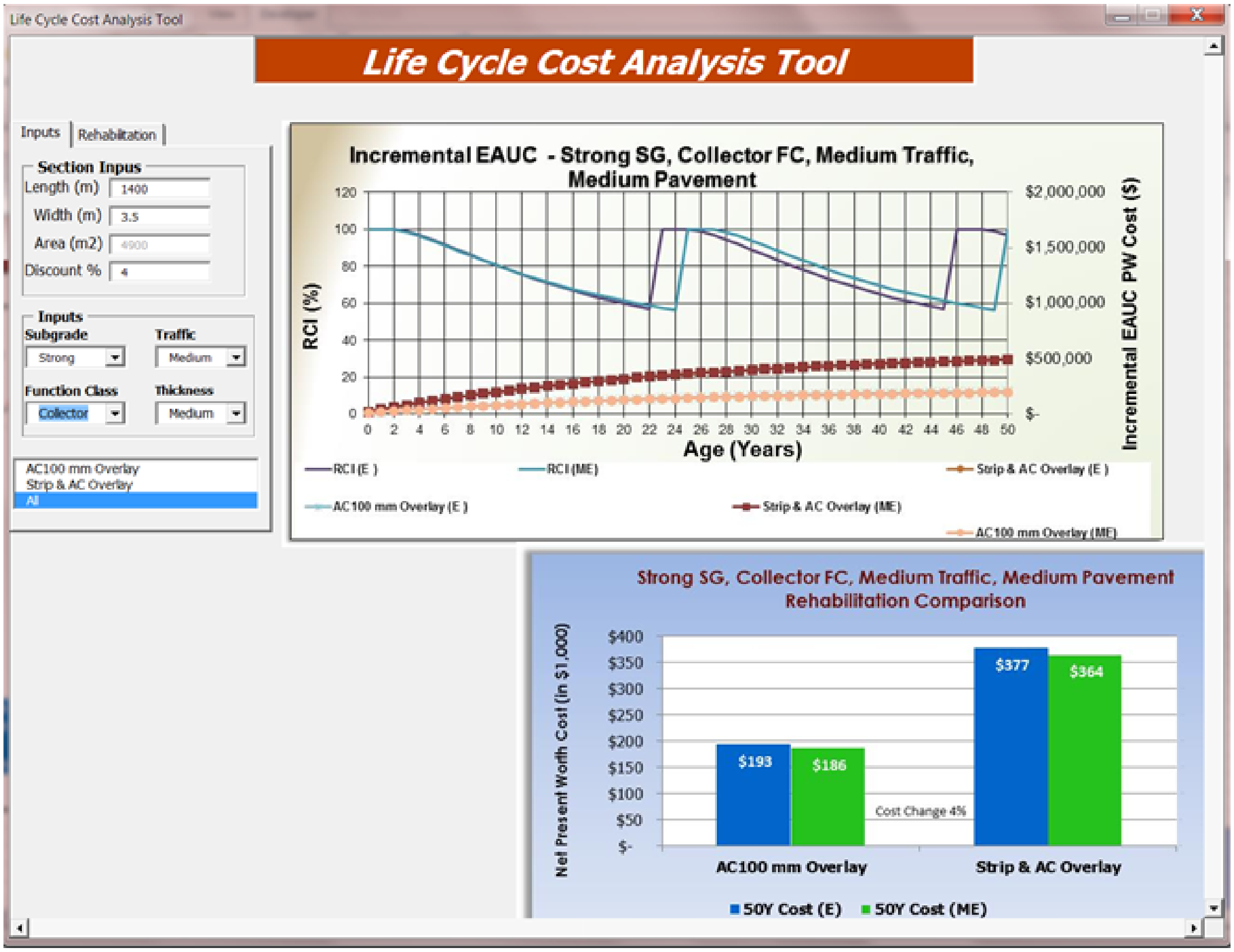


Figure 7-12: Model 8 Empirical vs Mechanistic Empirical LCCA Results (Collector Roads)

Arterial roads tend to deteriorate at a much faster rate compared to local and collector roads, as shown in Figure 7-13. The use of empirical models resulted in a 2% cost overestimation when compared to estimates using M-E models.

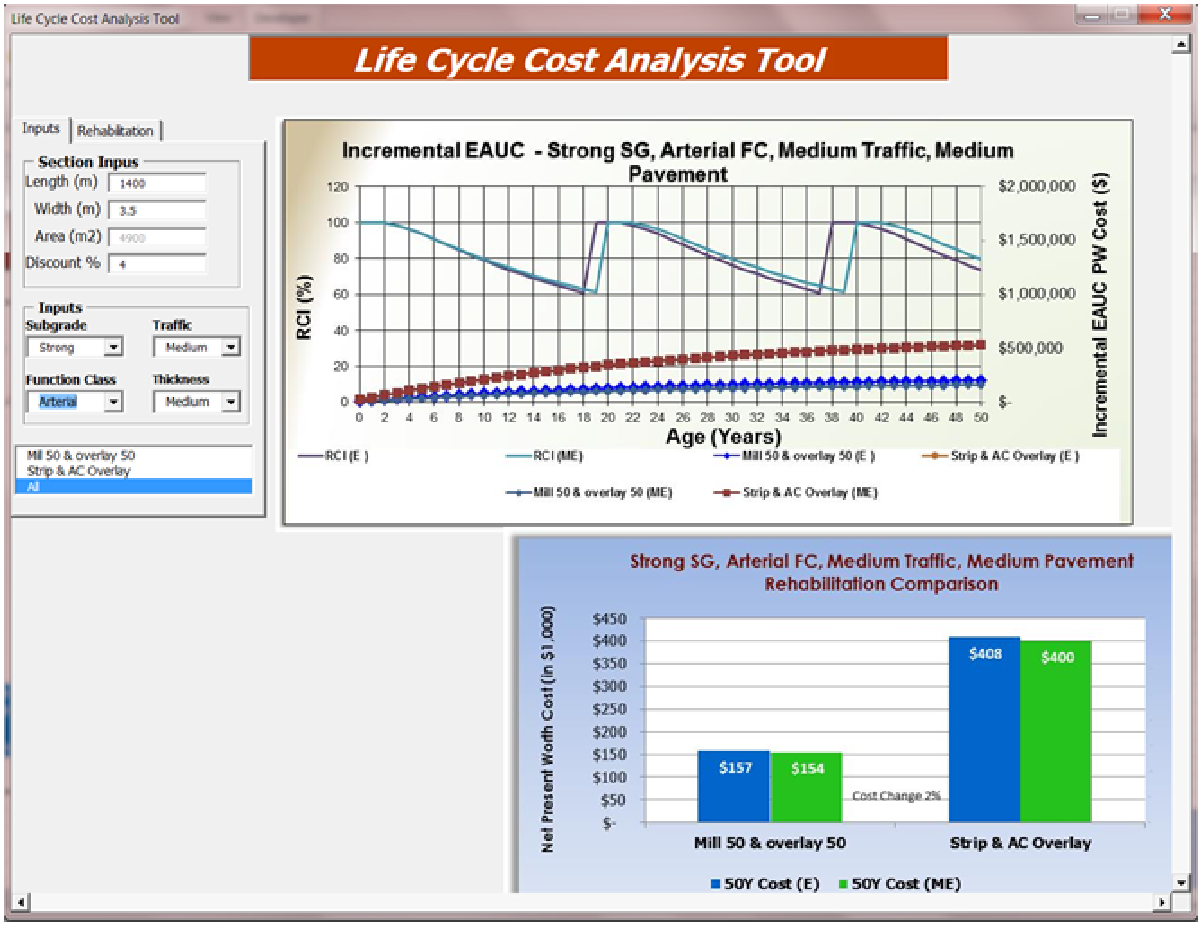


Figure 7-13: Model 8 Empirical vs Mechanistic Empirical LCCA Results (Arterial Roads)

7.4.4 Model 13 Analysis Comparison Results

Model 13 represents pavement deterioration associated with strong subgrade, low traffic and thick pavement. As can be seen from the RCI deterioration models for local functional classes, the empirical models tend to over-predict the trigger rehabilitation year later than expected compared to M-E models, and accordingly underestimates the present worth cost for the same alternative. There is a one-year difference in prediction between the trigger year for each model. However, differences in deterioration between the two models resulted in an insignificant difference in cost estimates for local roads, as shown in Figure 7-14, due to small differences in the service life.

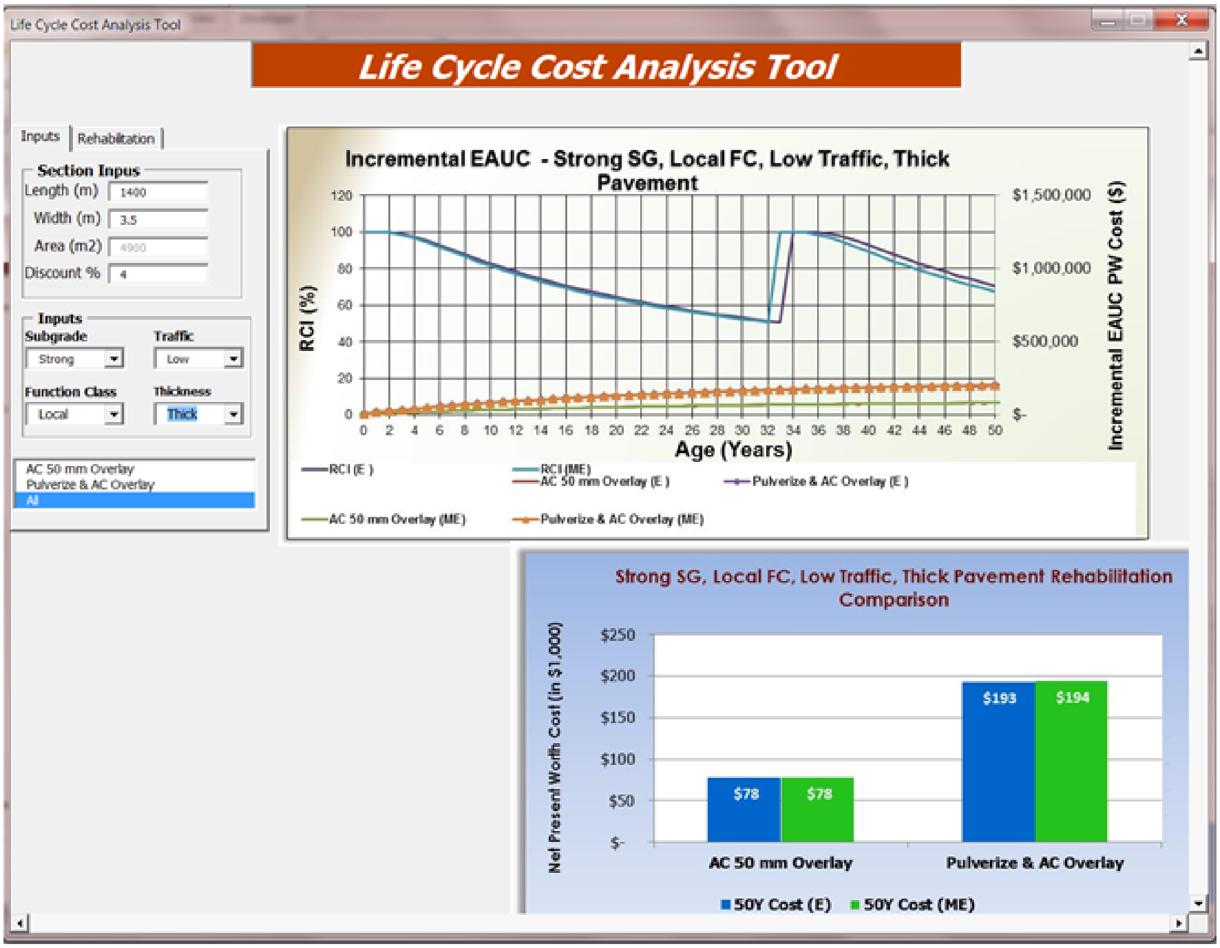


Figure 7-14: Model 13 Empirical vs Mechanistic Empirical LCCA Results (Local Roads)

For collector roads, even though the deterioration rate for empirical models was relatively similar to M-E models for the first few years after the rehabilitation, both models ended up having a different predicted service life. Similar to local roads, the empirical models tended to over-predict the service life when compared to M-E prediction by almost three years. The use of empirical models resulted in underestimating the cost by 3% when compared to estimates using M-E models, as shown in Figure 7-15.

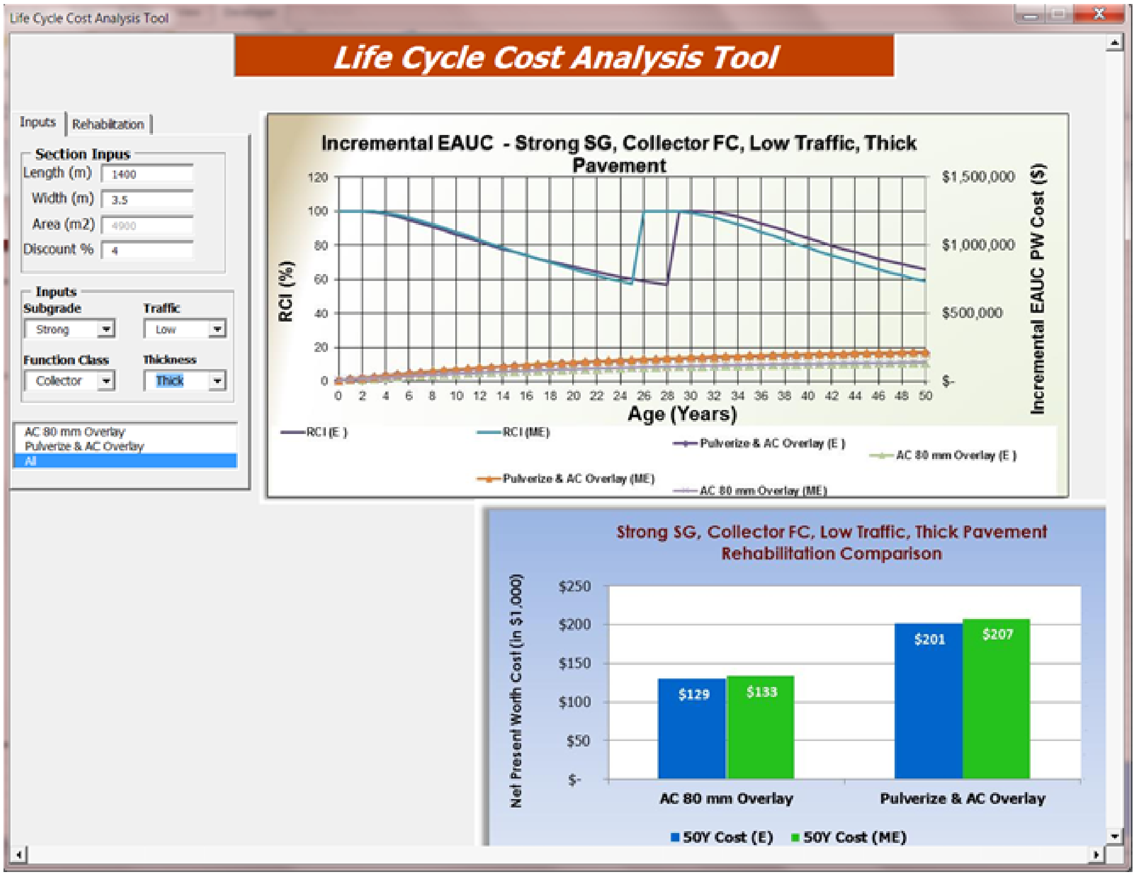


Figure 7-15: Model 13 Empirical vs Mechanistic Empirical LCCA Results (Collector Roads)

The arterial roads shown in Figure 7-16 have a reverse trend when compared to local and collector roads. As can be seen from the RCI deterioration models, the empirical model tends to under-estimate service life earlier than expected compared to M-E models, and accordingly, overestimates the present worth cost for the same alternative. For example, empirical models overestimated the cost for a full AC 100mm overlay strategy by an almost 11% difference.

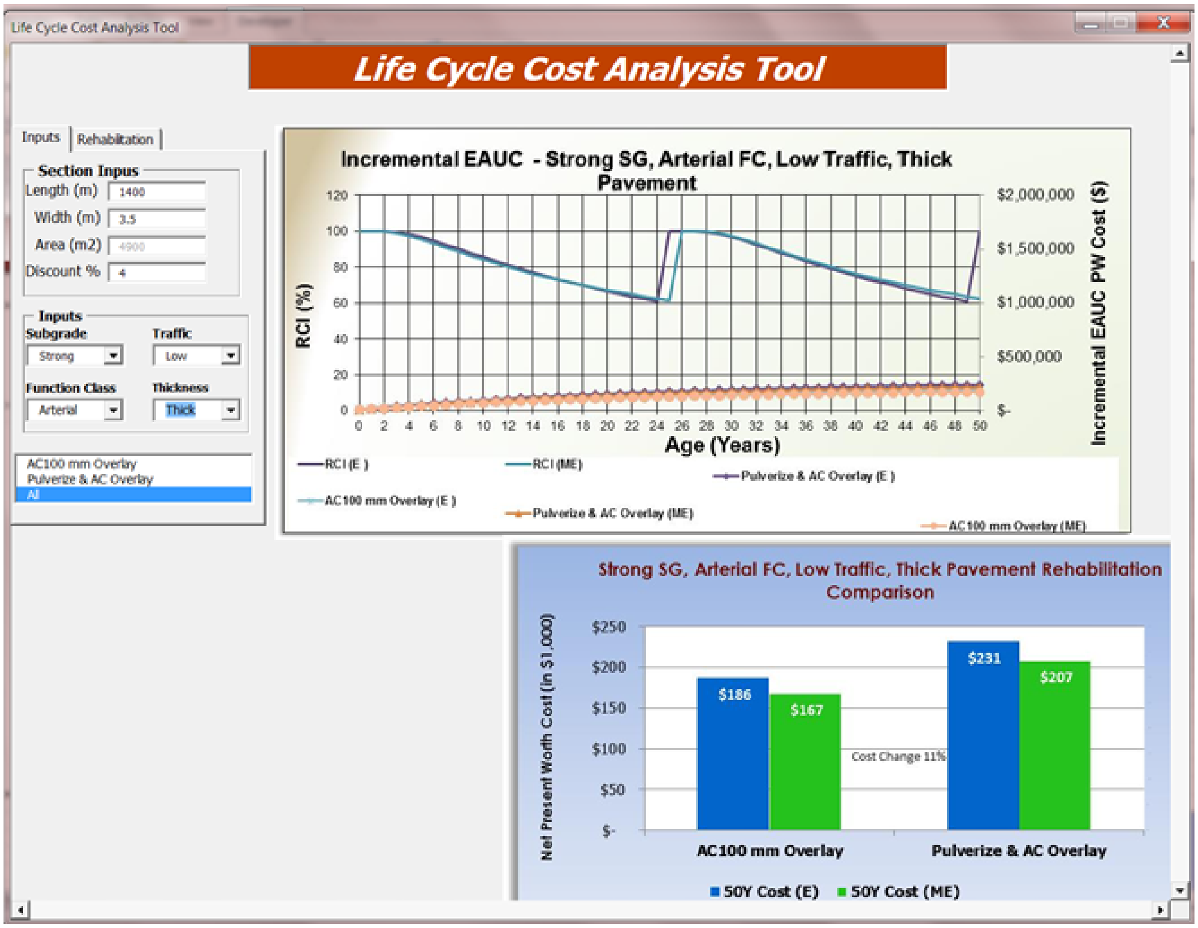


Figure 7-16: Model 13 Empirical vs Mechanistic Empirical LCCA Results (Arterial Roads)

7.5 OVERALL MODEL IMPACT COMPARISON

Figure 7-17, Figure 7-18 and Figure 7-19 show the difference in net present worth cost for all possible condition presented in the case study. The percentage in cost difference was calculated using the following equation:

$$Cost\ Difference\ (\%) \ = \frac{NPW\ (Empirical) - NPW\ (ME)}{NPW(Empirical)} \text{.......................................(Equation 7.1)}$$

Where:

$NPW(Empirical)$ is the total net present worth of the strategy over the analysis period using empirical deterioration models.

$NPW(ME)$ is the total net present worth of the strategy over the analysis period using mechanistic-empirical deterioration models.

Since the M-E deterioration models are more practical and realistic compared to traditional empirical models, they are used as the benchmark for comparison. In most cases, the empirical models tend to overestimate the net present worth cost compared to the newly developed M-E models. Only three conditions (Models 13 for collector, 14 and 18 for arterial) showed that NPW costs predicted using empirical models were less than NPW costs predicted using M-E models. The highest difference in cost estimates was noted in model 16 local, where the difference in estimate reached almost 27%. While a few models did not show any significant difference in cost estimates (0%), other models showed a reverse trend. The difference in cost estimates in non-critical models was relatively higher when compared to the difference in critical models.

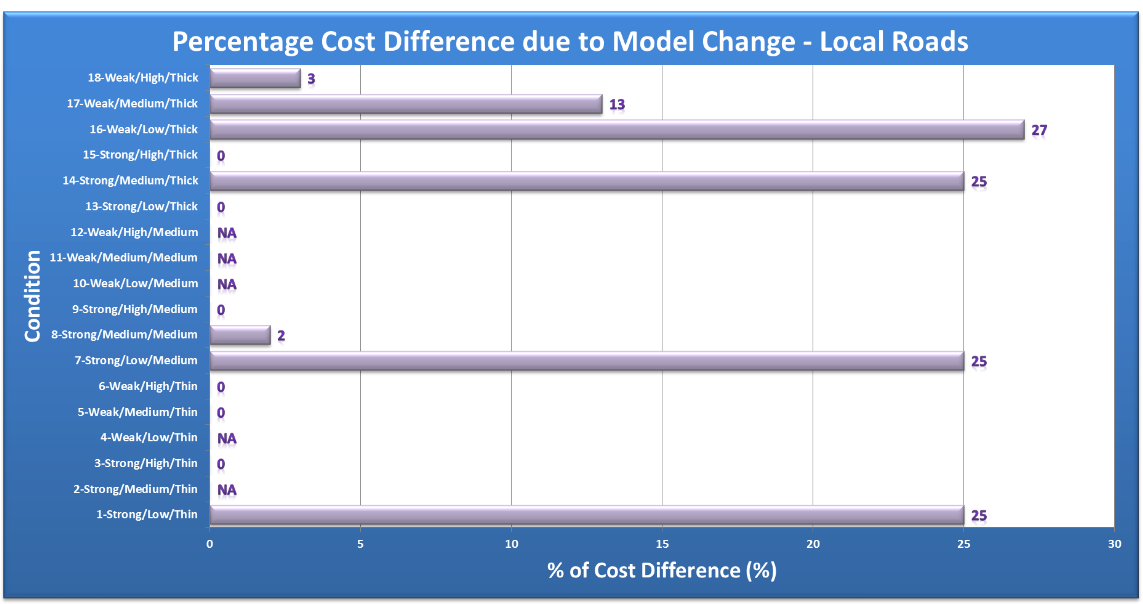


Figure 7-17: Estimated Cost difference by Condition for Local Roads

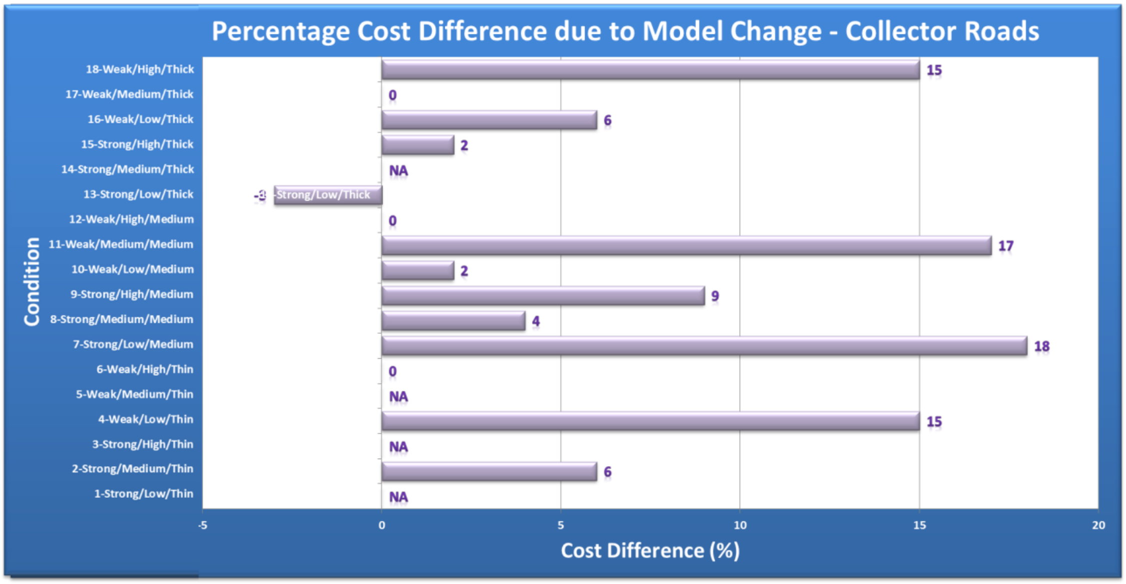


Figure 7-18: Estimated Cost difference by Condition for Collector Roads

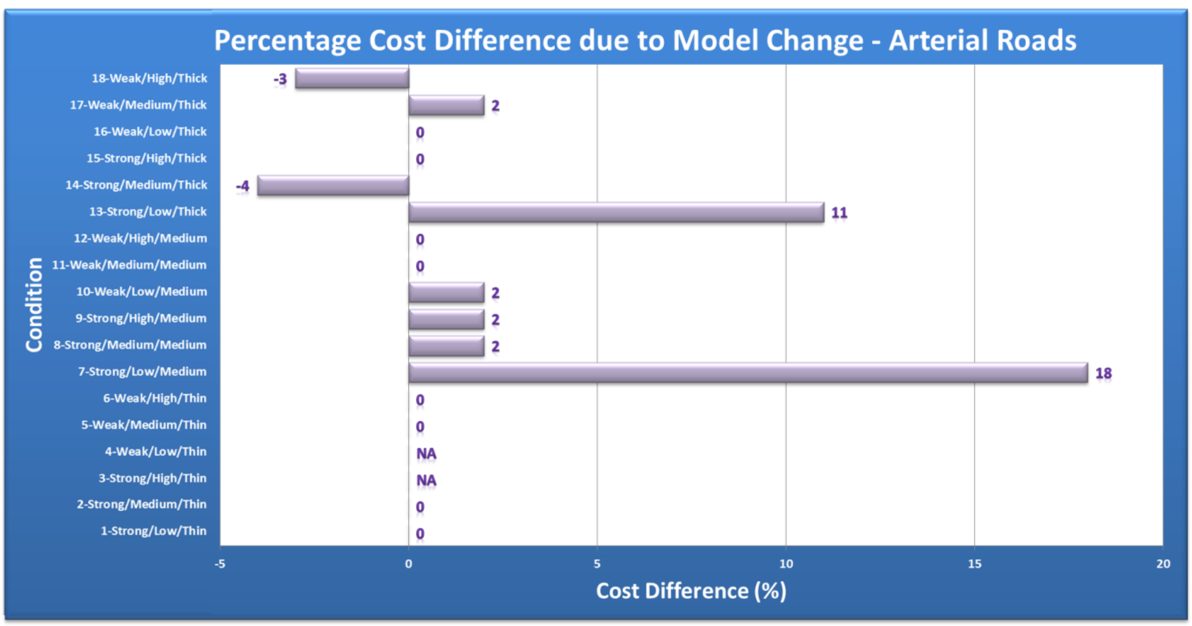


Figure 7-19: Estimated Cost difference by Condition for Arterial Roads

7.6 CONCLUSION

This Chapter presented a decision support tool that was programmed on an excel platform to encapsulate the developed decision-making framework procedures. The tool incorporates the recommendations and analysis from the LCCA performed to provide the most cost-effective alternatives, with all flexibility needed to modify project properties such as project geometry, discount rate or adding new treatment for future work. The tool provides the user with alternatives based on both empirical models and M-E models. This tool is intended to be used as a high-level planning tool at the project level, and the final decision on construction strategy should be based on detailed engineering analysis and design. The make-up of final decisions for pavement structure needs should be assessed in light of load carrying capacity and drainage conditions. The following section will provide comparison between empirical model and M-E model impacts at the network level.

8.0 Comparison between Empirical and Mechanistic Empirical Models at Network Level Analysis

8.1 INTRODUCTION

Deterioration models are commonly used in PMSs to account for pavement decay over time. Within a PMS context, these models predict when a segment of the road reaches a condition that needs rehabilitation. The built-in decision trees, in addition to deterioration models, help select the most cost-effective treatment among different rehabilitation options, based on an expected service life to attain the best set of alternatives for the network. In order to validate the previously developed enhanced empirical models and the new M-E models at the network level, an evaluation through a full PMS implementation process is required. To achieve this goal, two budget scenarios were implemented at the network level of analysis. The first scenario was based on enhanced empirical models, while the other one employed the M-E models, and a comparison between the two strategies was conducted. Data collected from one of the cities in Southern Ontario was used as a case study to compare the two model-based scenarios and to demonstrate how both models can influence decision-making for future funding.

Initially, a Micropover® application for PMS implementation was selected to implement such a comparison. However, the regression deterioration models built in Micropover® did not allow loading the developed models that were based on customized sigmoidal models. Therefore, RoadMatrix®, one of the most commonly used PMS software in the market, was selected to accomplish this task instead. RoadMatrix® is a comprehensive tool used by various municipalities across North America to create optimized asset management plans. It was designed specifically for municipal agencies to meet their decision-making needs in an efficient manner. It features a logical network inventory module to provide instant access to road data, and has the capability to view and update information by street, district, or functional class. In addition, Roadmatrix® can store roadway geometry, traffic data, structural composition, work history, and right of way assets, including sidewalks. It accommodates multiple types of industry standard condition surveys and inspections, and captures roughness (IRI), pavement distress, rutting, and structural (FWD) data. The most powerful tool of the software is the budget analysis module that explores multiple scenarios and quickly investigates the current present status of the network, as well as how much spending is needed for the next programming period to reach a target service level.

8.2 LOADING DETERIORATION MODELS INTO MUNICIPAL PAVEMENT MANAGEMENT SYSTEM

Roadmatrix® stores data in an SQL server database format. Appendix I shows the SQL query scripts that were used to enter the developed empirical models and M-E models into the Roadmatrix® system. It should be noted that Roadmatrix® needs 50 years of data points for each model category in order to run the analysis. Since the models developed in this study had data for only 30 years, the value of year 30 was extended until year 50. However, a road section is typically not left for more than 30 years without maintenance.

8.3 PAVEMENT MANAGEMENT SYSTEM IMPLEMENTATION: A CASE STUDY

8.3.1 Overview

Historical condition data for the city of London, Ontario was used to evaluate the developed models. The network used in the analysis consists of approximately 1,786 centerline kilometres of paved roads, of which 1,676 km (or 3,708 lane kilometres) are constructed as flexible pavement. It is important for transportation agencies to maintain and update road condition data on a regular basis. The advantages of continuously maintaining the pavement management program for municipalities and transportation agencies are:

- To collect the pavement performance data required to assess the current condition of the selected agency's road network;

- To estimate the future condition of the pavement network and to determine the rehabilitation requirements over the next programming period;

- To identify feasible rehabilitation alternatives for each road section and, based on this information, assemble rehabilitation programs for various funding scenarios; and

- To estimate the impact that these programs will have on the condition of the network over the next programming period.

Ride comfort data was loaded into the RoadMatrix® and an analysis was conducted to determine the present status of all roads in terms of Pavement Quality Index (PQI). The analysis was accomplished using the software's loaded empirical and mechanistic-empirical pavement deterioration model, as previously explained to estimate the rehabilitation requirements of the road network for a ten-year period, beginning in 2014. From these results, pavement rehabilitation programs were developed using a life cycle economic analysis to maintain the network performance at PQI = 65 condition, and to estimate the annual road rehabilitation budget needed to achieve this goal using the two model schemes.

8.3.2 Network Sectioning

Implementation of a pavement management system requires the pavement network to be divided into a series of homogeneous sections that share the same traffic pattern, pavement thickness, and subgrade condition for each functional class. This step is essential to allow the preloaded deterioration model to predict future conditions for sections having the same category, as classified by model classes.

8.3.3 RoadMatrix® Implementation and Analysis

Since empirical models and M-E models were only developed for flexible pavement types, it was essential to create a subset of the entire network that accounts only for sections with flexible pavement type and only for local, collector, and arterial roads. Using the built-in query in RoadMatrix®, a subset that consisted of 1,676 centerline kilometres (or 3,708 lane kilometres) was generated. The progression of tasks associated with the RoadMatrix® implementation is depicted in Figure 8-1.

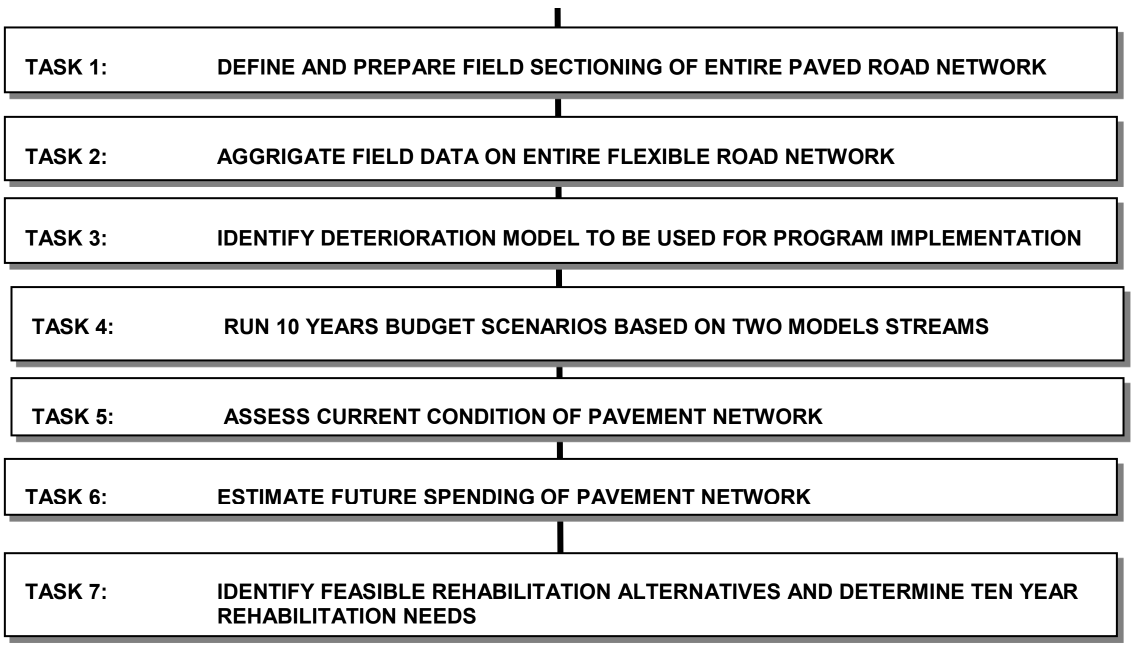


Figure 8-1: Progression of Tasks for RoadMatrix Implementation

8.3.4 Pavement Quality Index (PQI)

The PQI provides an overall indication of the condition of a pavement with regard to present and future service to the user. Generally, the PQI is derived from other pavement condition indices such as the RCI, the SDI, and (Structural Adequacy Index) SAI. The PQI represents a combination of the sectional RCI, SAI, and SDI values. Each municipality uses its own unique formula to formulate PQI scores based on a different condition index collected by the agency and how frequent the annual condition data is available. For instance, if the agency only collected distress data (no structural or roughness data), then only SDI scores will be used to represent the overall pavement quality index (PQI).

Since this case study is concerned about RCI models and the assessment of the newly developed mechanistic-empirical models, the PQI was modeled to have RCI scores (i.e., PQI = RCI). PQI scores therefore varied from 0 to 100, where 0 represented the poorest possible pavement condition and 100 represented the best possible pavement condition.

8.3.5 Performance Prediction Modeling and Needs Analysis

Needs analysis was calculated based on PQI scores. The PQI values of pavements typically decrease over time. In order to estimate the future rehabilitation requirements of a pavement network, it was necessary to model the deterioration of PQI values. When PQI is modeled to have RCI scores, PQI will consequently share the same factors that influenced RCI. The PQI deterioration models were therefore classified in the current implementation based on traffic loading patterns, the properties and thicknesses of the pavement structure layers, and the subgrade condition. This resulted in eighteen possible PQI classes for each functional class, as defined previously for RCI.

8.3.6 Priority Programming Analysis

An approach utilizing decision trees to identify feasible strategies was employed to implement a ten-year rehabilitation program that maximized the benefit of each dollar spent while considering the PQI quality constraints, as specified every year during the programming period. In addition, a life cycle economic analysis was used to assess the relative effectiveness of each strategy. The final result of this analysis was an improvement program stating which pavement sections are recommended for rehabilitation, the year in which rehabilitation should be implemented for each section, and the type of rehabilitation strategy recommended for each section. The rehabilitation analysis required the identification of possible rehabilitation strategies for each section and their associated unit costs. Decision trees identified the appropriate strategies to be considered under a range of conditions.

8.3.7 Budget Analysis

The decision tree analysis determines the alternatives for rehabilitation purposes. Using these alternatives, the unit costs, and the deterioration prediction model, a life cycle economic analysis was used to implement rehabilitation strategies in a way that the benefits of capital expenditures were maximized while maintaining the overall network condition constraints specified for each year in the programming period. Because actual unit costs were unavailable, costs were assumed for different treatments. The objective of the study was to evaluate the impact on estimated budgets due to model change rather than produce actual budget estimates.

Two separate 10-year rehabilitation programs were defined in the system to be used in the budget analysis:

- Maintain network condition at PQI = 65 using empirical models
- Maintain network condition at PQI = 65 using mechanistic-empirical models

During the various program implementation runs, a rehabilitation project for a section can be executed in its needed year or any time thereafter, depending on its cost effectiveness relative to other potential projects and on the available budget to maintain network condition PQI = 65. An inflation rate of 3% was assumed throughout the entire analysis.

8.3.8 Analysis Results

The following sections discuss the present status of the road network. Present status analyses were performed using the subset of “Flexible-All”, which includes approximately 1,676 centerline kilometres (or 3,708 lane kilometres) of flexible roads only. This subset has been used for all subsequent analysis and comparison.

8.3.8.1 Present Status: Riding Comfort Index (RCI) Analysis

Figure 8-2 shows the present distribution of RCI values, weighted by lane kilometres. The analysis network has a mean RCI of 63.4. As can be seen, the majority of the network falls between RCI = 50 and RCI = 80. The results indicate that more than 38% of the road network (weighted by lane kilometres) exhibits acceptable ride characteristics above 80, while a small portion (approximately 4% of the road sections) have poor ride quality (RCI below 40), based on the most recent roughness data collected. It should be noted that the total length shown is Figure 8-3 is the length of the lanes in *km*, which is the centerline length of each road multiplied by its existing number of lanes.

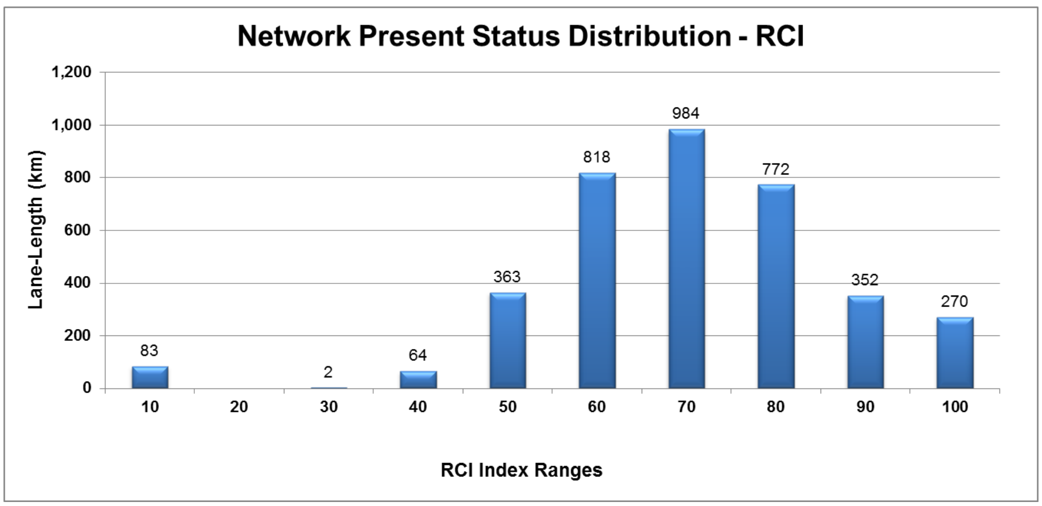


Figure 8-2: RCI Network Present Status Distribution

8.3.8.2 Present Status: Pavement Quality Index (PQI) Analysis

Each functional classification has been assigned a minimum acceptable PQI trigger value in the RoadMatrix® decision trees. This trigger value was used to determine the time when a particular road section in a given functional class group requires some form of preventative rehabilitation. Since PQI is assigned to be equal to RCI, the trigger values for RCI were used for PQI scores to determine the rehabilitation alternatives. For each road functional class, Table 8-1 shows the average PQI and the total lane kilometres that are at or below the minimum acceptable PQI value, based on the most recent data collected.

Table 8-1: Summary of PQI Distribution and Deficiencies by Functional Class

FUNCTIONAL CLASS	AVG PQI	MIN PQI	SECTIONS	LANE-KM
Arterials	68	60	1,437	1,311
Collectors	65	55	2101	650
Local Streets	62	50	4,943	1,747
NETWORK TOTAL			**8,481**	**3,708**

8.3.9 Improvement Needs Analysis

The year in which the PQI of a section is equal to or below the minimum acceptable PQI level is defined as the Need Year of that section. The Need Year distribution for the pavement network is presented in Figure 8-3 using empirical and M-E models, respectively. Using the empirical models shown in Figure 8-3, the distribution shows that 1,278 lane kilometres, or approximately 34.5% of the network, was in need of rehabilitation in 2014. In subsequent years, through the end of the 10-year analysis period in 2023, the network needs range from about 8% to 11% annually. Overall, approximately 4,289 km of the analysis network has been identified as expecting to require some form of rehabilitation during the upcoming ten-year analysis period.

Using the mechanistic-empirical models shown in Figure 8-3, the distribution shows that only 1,039 lane kilometres, or approximately 28% of the network, was in need of rehabilitation in 2014. In subsequent years, through the end of the 10-year analysis period in 2023, the network needs range from about 5% to 7% annually. Overall, approximately 2,931 km of the analysis network has been identified as expecting to require some form of rehabilitation during the upcoming ten-year analysis period.

The previous results illustrate that both models showed the entire network needs some form of rehabilitation in the next ten years, but with different needs distributions over the ten-year programming period. This analysis indicates that empirical models overestimate the number of sections in need of rehabilitation, especially in the first year, compared to mechanistic empirical models, which means more spending to improve network conditions when empirical models are used in the analysis. Figure 8-4 to Figure 8-6 show the breakdown of the annual network distribution needs for each functional class. This analysis shows that local roads will receive most of the rehabilitation activities in the first year of analysis period using either empirical or mechanistic-empirical models, which represents 17% or 11% of total network respectively.

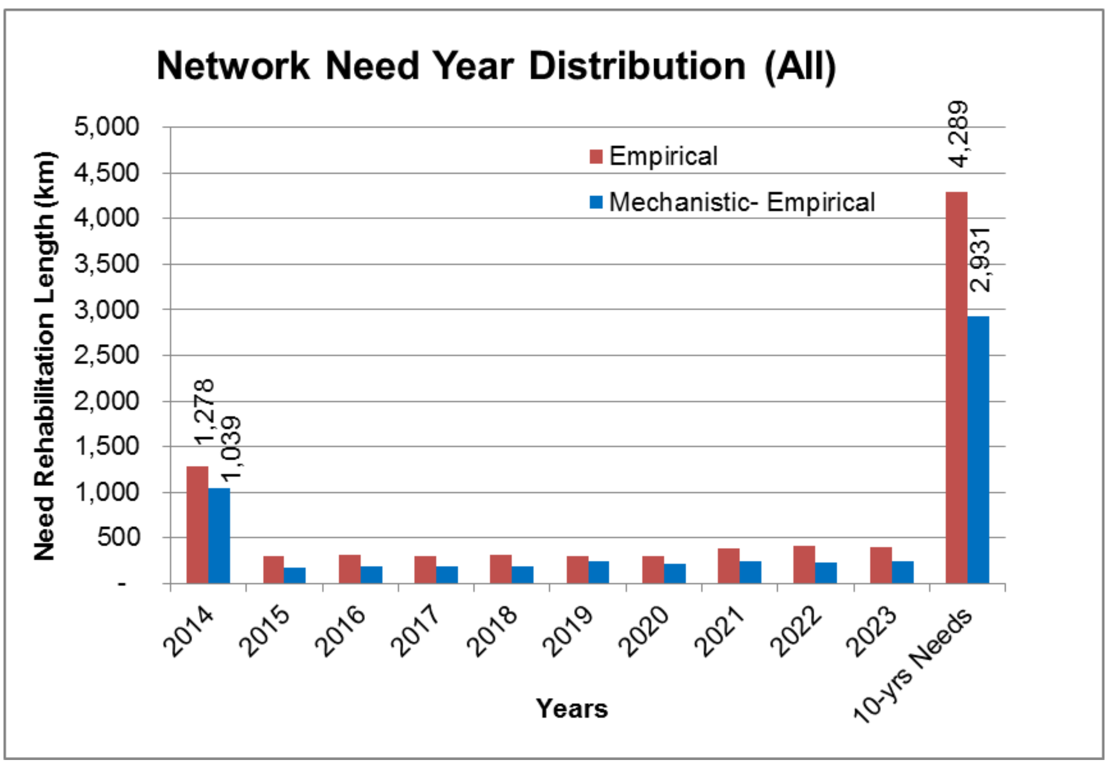


Figure 8-3: Need Year Distribution using Empirical vs. ME Models

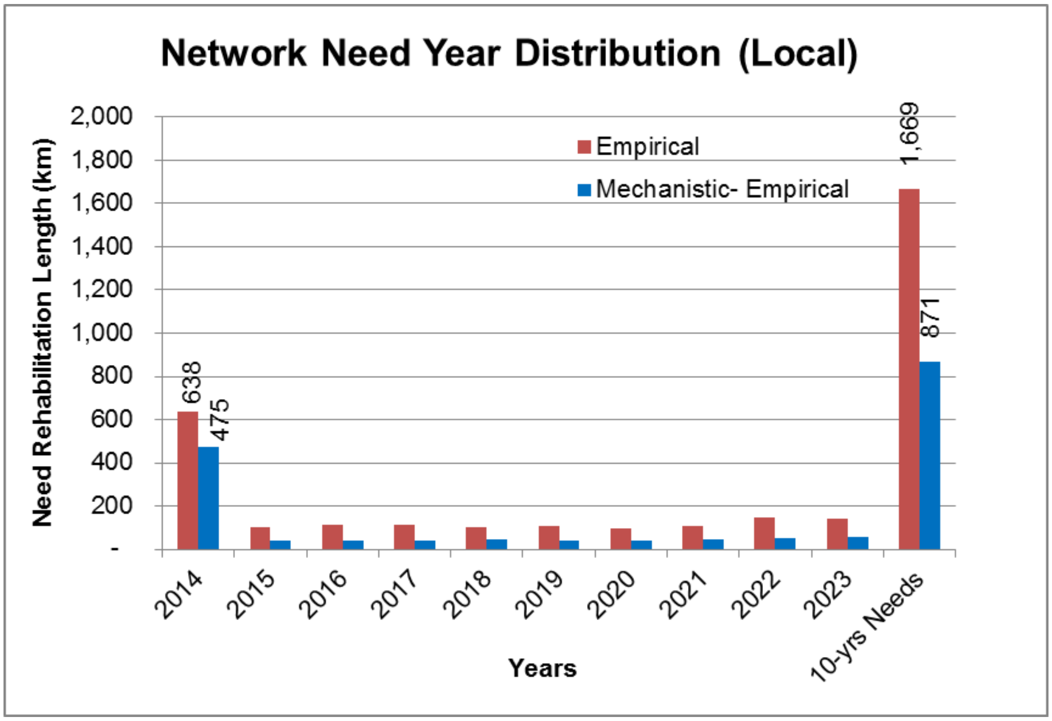


Figure 8-4: Need Year Distribution using Empirical vs. ME Models (Local)

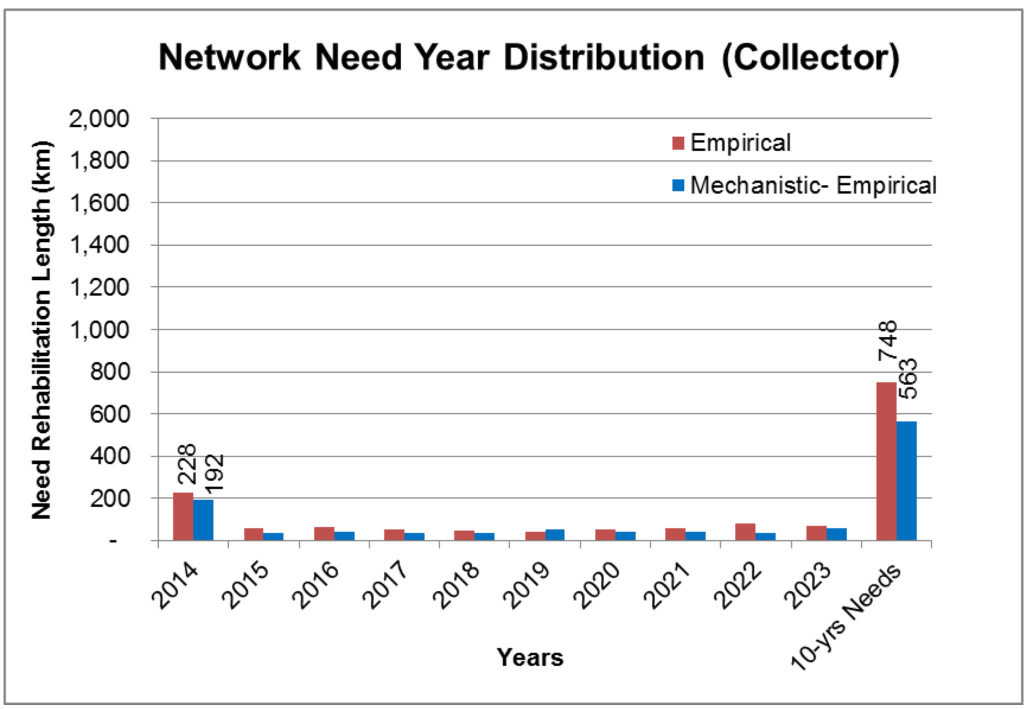


Figure 8-5: Need Year Distribution using Empirical vs. ME Models (Collector)

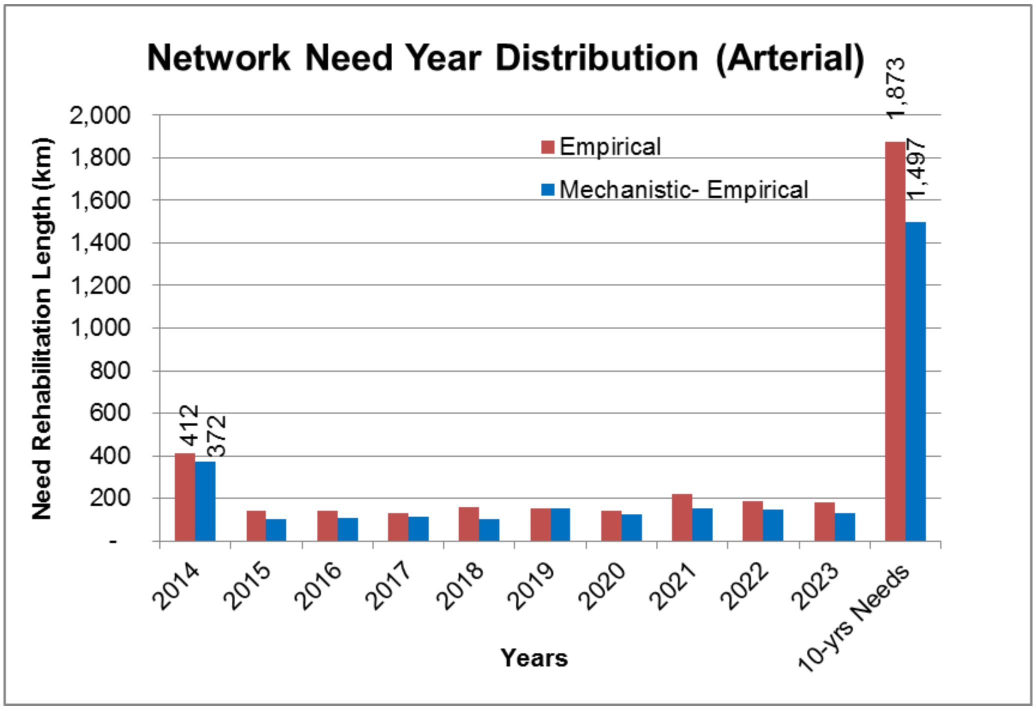


Figure 8-6: Need Year Distribution using Empirical vs. ME Models (Arterial)

8.3.10 Priority Programming Analysis

The Priority Programming Analysis was conducted using two different budget scenarios. The budget streams were defined as follows:

- Maintain Network Condition PQI = 65 using empirical models
- Maintain Network Condition PQI = 65 using mechanistic-empirical models

8.3.11 Network Performance

Using empirical models, as shown in Figure 8-7, the network average PQI (Budget-Driven) over the program period is 65. At the end of the program, the network PQI is 65 with 16.3% of the pavement network falling below the minimum acceptable PQI. If each section in the network subset had been rehabilitated in its needed year (Need-Driven), the network average PQI would be 69.4. In this case, at the end of the program, the network PQI would be 67.6 with no section (0%) falling below the minimum acceptable PQI. The total required budget is $679,586,194. If no rehabilitation is performed on the pavement network (Do-Nothing) targeted by this budget, the network is expected to have an average PQI of 50.2. In this case, at the end of the program, the network PQI would drop to 42 with 92.2% of sections falling below the minimum acceptable PQI.

On the other hand, when mechanistic empirical models are used, as shown in Figure 8-8, the network average PQI (Budget-Driven) over the program period is 65. At the end of the program, the network PQI is still 65, with 11.8% of the pavement network falling below the minimum acceptable PQI. If each section in the network subset had been rehabilitated in its needed year (Need-Driven), the network average PQI would be 68.2. In this case, at the end of the program, the network PQI would be 65.8 with 0% falling below the minimum acceptable PQI. The total required budget is $463,309,948. If no rehabilitation is performed to the pavement network (Do-Nothing) targeted by this budget, the network is expected to have an average PQI of 55.4. In this case, at the end of the program, the network PQI would drop to 49.9 with 68.1% of sections falling below the minimum acceptable PQI.

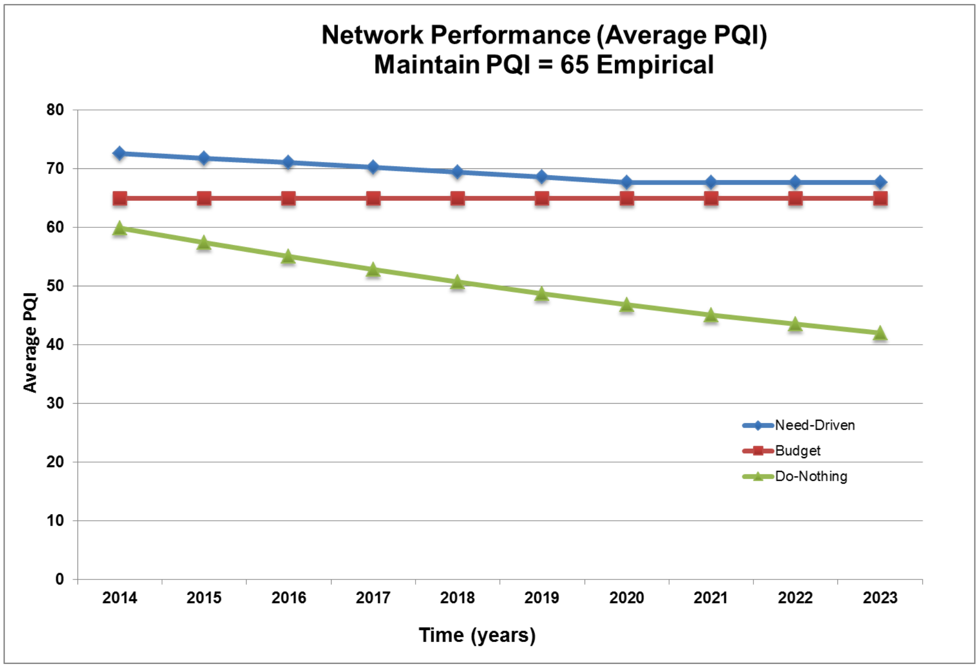


Figure 8-7: PQI Network Performance using Empirical Models

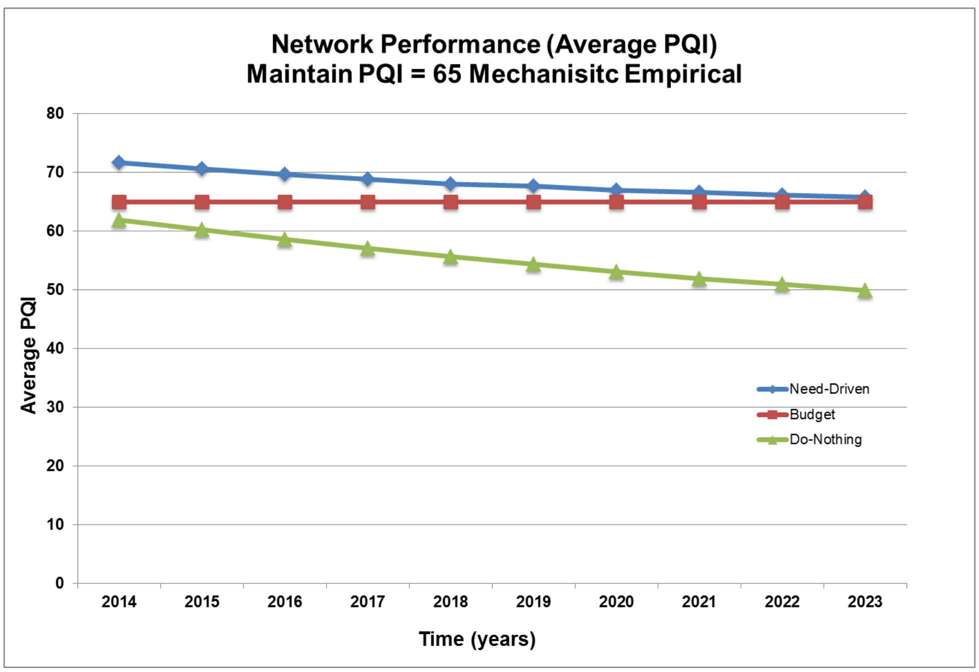


Figure 8-8: PQI Network Performance using Mechanistic-Empirical Models

8.4 COMPARISON OF BOTH BUDGET SCENARIOS

The difference between the two budget scenarios are summarized in Figure 8-9 by functional class, in which the network average PQI was calculated throughout each 10-year program period, assuming that the selected rehabilitation strategies had been implemented each year. In each scenario, the budget was optimized for different rehabilitation options in order to maintain the overall PQI network at 65 each year. The percentage of saving or expense was calculated at each year using the following fomula:

$$Saving\ or\ Expense\ (\%)\ at\ year\ (i\ )\ = \frac{Budget\ (Empirical) - Budget\ (ME)}{Budget(Empirical)} \ldots\ldots\ldots\ldots \text{(Equation 8.1)}$$

Where:

$Budget(Empirical)$ is the total expected budget to spend at $year\ (i)$ using empirical deterioration models.

$Budget(ME)$ is the total expected budget to spend at $year\ (i)$ using mechanistic-empirical deterioration models.

Even though both budgets were implemented with the same goal of keeping the network at the same condition and for the same subset sections of the network, it was evident that using the newly developed M-E models helped save money and more accurately predict future spending. This is depicted in Figure 8-9, which illustrates differences in spending differences between the two model schemes. With the exception of years 2016 and 2019 budgets for collector roads, the use of ME models introduced savings to transportation agencies compared to empirical models. The percentage of saving for local roads was noted to be higher rate in first years of analysis period when most of the budget is consumed compared to last few years of the analysis period. In the first year, it was noted that a relatively higher budget was spent when empirical models were used to bring the network to acceptable levels than that spent when mechanistic empirical models were used, with the budget stabilized during the following year. This was expected since empirical models showed a greater declining rate of deterioration overall in the first few years compared to those predicted by M-E models. However, the current analysis helped quantify the difference in dollars between the two models' utilization.

These results demonstrated how prediction models play an important role in predicting future expenditure for municipal and transportation agencies. It also shows how M-E models supersede traditional empirical models in predicting pavement performance and may introduce savings to the public in some cases. It is important to note that M-E models will not always present budget savings to transportation agencies, as demonstrated in the current case study. Instead, it will present more realistic spending estimates based on more factual prediction models. The analysis demonstrates how important is to use deterioration models that truly represent the real condition of the overall network, and how to accurately predict future pavement performance as shown when mechanistic empirical models were used in the current case study. This will definitely assist transportation agencies to accurately predict their future funding and network needs.

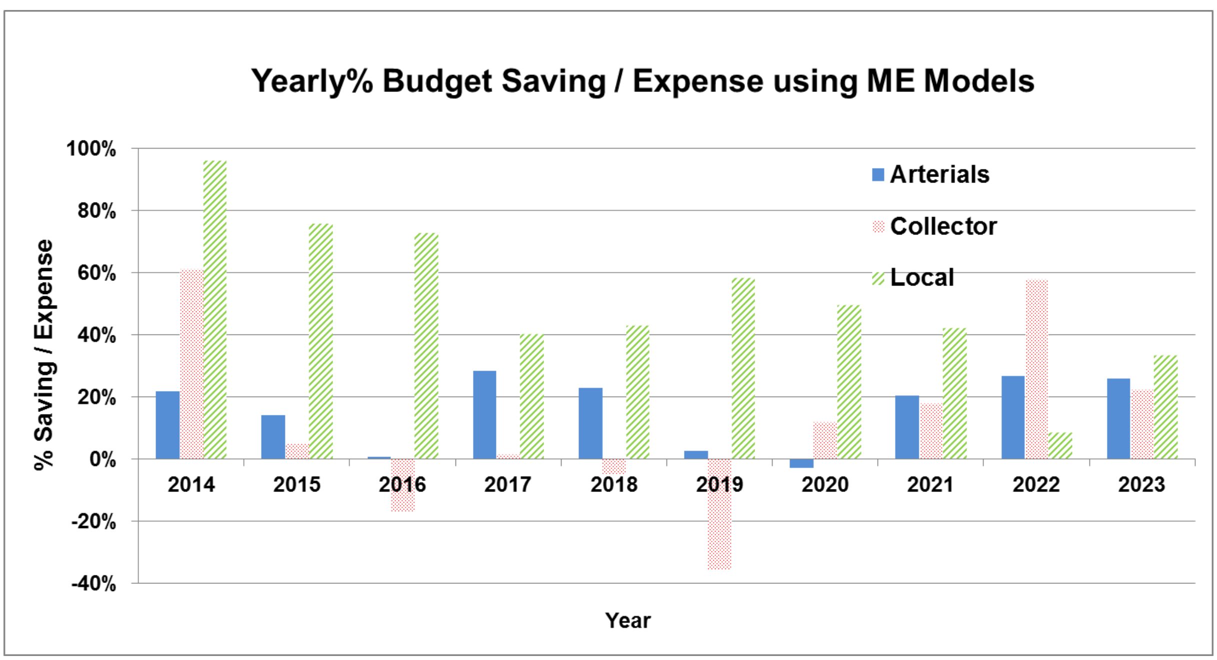


Figure 8-9: Empirical vs. Mechanistic-Empirical Yearly Budget Spending

8.5 SUMMARY

This Chapter summarized the comparison between the two types of models at the network level of analysis. Two budget scenarios to maintain network condition at an overall score of pavement quality index 65 were implemented, based on the two model streams. Comparison between the two budget expenditures demonstrated that budget scenarios were sensitive to the models used to aggregate rehabilitation strategies at each road section. The comparison illustrated how crucial it is to use realistic models during budgeting and planning for future expenditure.

9.0 Conclusions, Research Contributions and Recommendations for Future Research

9.1 INTRODUCTION

Performance prediction models are essential components in any efficient pavement management system. Accurately predicting pavement performance over time is crucial for better planning and budgeting of future maintenance and/or rehabilitation activities. Recently, with the evolution in pavement data collection technology, transportation agencies have started to collect performance data on a regular basis and at more frequent cycles. However, most of these agencies, especially at the municipal level, only collect data for present pavement condition evaluation, while limited effort has been made to use performance data collected over previous years. Even with the presence of performance data, transportation agencies are faced with the dilemma of limited construction activity data essential to developing realistic performance models.

The current research developed new enhanced empirical models using the performance data already collected and stored in various municipal PMSs. The proposed enhanced models are innovative in their ability to employ engineering judgment in the absence of historical construction/maintenance data to develop more realistic and practical deterioration models. A linear programming optimization technique was employed to fit the sigmoidal model and to minimize discrepancies between the measured and predicted data. The models were developed for two types of pavement performance indices: the Ride Comfort Index (RCI) and the Surface Distress Index (SDI). RCI is derived from the International Roughness Index (IRI), which represents the traveling public's opinion of the smoothness of the road and hence, the quality of service and comfort provided by a pavement.

On the other hand, the SDI has been derived from different measured distresses that are rated later, based on their severity and their extent, to determine a final SDI score for homogenous sections across the agency's network. Historical data were categorized based on the design of experiment (DOE) that accounts for different parameters found to highly impact pavement performance. Traffic pattern, subgrade condition, and pavement thickness were identified through literature review to be the most significant parameters greatly influencing such performance. Accordingly, models were developed for different category combinations in the DOE.

Condition data collected from cities in Western Canada, such as Burnaby and Nanaimo in British Columbia, was used to develop enhanced empirical models for the western region that were later compared to the ones developed for Eastern Canada, in order to evaluate the impact of regional and environmental changes on pavement performance. The comparison showed performance variations in both regions, which suggested that regional and climatic changes have a significant impact on performance. The models developed for the western region provide preliminary models that can be used currently by different municipalities that share similar environmental conditions. These models can be further enhanced using local and site-specific data.

Recent changes in pavement design practices from an empirical design approach to a mechanistic-empirical design have driven many transportation practitioners to evaluate pavement designs based on M-E principles. The mechanistic-empirical design guide (MEPDG) program was initially implemented to provide engineers with a tool to design pavement based on M-E concepts. It was followed by the final product M-E AASHTOWare® program. Several studies were carried out to compare designs based on both traditional empirical and new M-E concepts. However, no efforts were made to investigate the application of the performance models incorporated within the MEPDG to pavement management system implementation. The use of M-E models derived from fundamental engineering properties and mechanistic theory is expected to provide more realistic models when compared to empirical models.

This research developed a second set of performance deterioration models based on M-E principles. In order to develop such models, MEPDG needs to first be locally calibrated to site-specific conditions. Different sections were therefore selected for calibration to sites in Ontario. The data required to execute MEPDG pavement design was extracted from different municipal pavement management systems. Measured roughness data extracted from PMSs was used to locally calibrate the selected sites. Traditional calibration techniques using the “trial and error” approach are found to be time consuming and lack the driving mechanism necessary to guide the search to achieve the optimum calibration coefficients that converge the predicted IRI to the measured value. Therefore, an MEPDG engine was developed to automate the calibration process. The engine uses send key commands to open the MEPDG program, to modify calibration coefficients, to run the analysis, to close the program, to read the MEPDG output files, and finally to store the results in the database. The advantage of automating the MEPDG calibration process gives transportation experts and pavement researchers the opportunity to employ different optimization techniques, which was not possible using traditional calibration approaches.

The linear programming optimization technique built in the Excel Solver was initially used to solve the optimization problem. However, it was found that the Solver conflicted with the MEPDG outputs that were using Excel as an output platform. Genetic Algorithm (GA) optimization technique was found to be more suitable for the calibration problem. A GA routine was coded to use the four roughness calibration coefficients as the genes for GA chromosomes. The process was repeated for each class combination to find the optimum calibration coefficients. The predicted roughness resulted from the GA showed promising results when compared to measured roughness, which suggested that GA is a suitable tool for MEPDG local calibration problems.

The developed models in this study were validated at both the project and network level of analysis. At the project level, a decision-making framework was established to provide a realistic tool for municipal engineers to compare different rehabilitation alternatives based on both empirical and M-E models. The tool provides a comprehensive life cycle cost analysis for different alternatives based on the different models' schemes. In order to further verify the models, a case study was used for one of the cities in Southern Ontario to implement two budget scenarios at the network level of analysis. The objective was to maintain network conditions at a performance index of 65, using the two model schemes. The budget analysis results demonstrated how the migration from empirical models to M-E models impacted budget needs during the analysis period.

9.2 RESEARCH CONTRIBUTIONS

Based on current developments, this research makes the following contributions:

- **Deterioration Model Development for Municipalities in Canada:**

  The literature review showed that no deterioration models have been developed for municipalities. Most of the research and industry efforts were devoted to model development solely for large-scale agencies such as federal or provincial roads. In addition, it has been observed that the majority of municipal agencies currently use old and outdated models that are based on limited historical data. Some municipalities use models that have been developed for nearby large agencies, which may not reflect the current condition of their own network. This research is unique in its approach as the first attempt to use local historical data stored in different municipal pavement management systems to develop performance models that are more representative of the network condition. The developed performance models address various parameters that are commonly known to influence pavement performance.

- **Development of Enhanced Empirical Models:**

The current research employs linear programming optimization techniques to fit measured data into a sigmoidal model. The flexibility of sigmoidal models and the presence of three model parameters (a, b, and c) allows the application of the selected optimization technique to find the optimum prediction model that minimizes the discrepancy between the predicted and measured data.

- **Incorporation of Expert Knowledge in Deterioration Models Development:**

The current research presents a methodology to overcome the lack of historical construction and maintenance data needed to develop the performance model. The optimization process is constrained by the pavement service life, as obtained from pavement engineers, and is incorporated into the model. These constraints are flexible in their nature and can be customized to reflect other conditions based on the knowledge collected in cases under investigation.

- **Better Understanding of Different Pavement Performance in Eastern and Western Canada Regions:**

The current research provides enhanced prediction models for Western Canada compared to those developed for Eastern Canada. Comparison between both models for each performance index reveals variation in pavement performances. Comparison at each class helps understand the behaviour of pavement performance and identify terminal service life for the two regions. The use of more historical data in the western region will enhance the model developed in this study.

- **Deterioration Model Development based on Mechanistic-Empirical Concepts**:

The current research develops new performance deterioration models that are based on M-E concepts. These models are presumably more representative of pavement performance compared to traditional models based on empirical concepts.

- **Automation of the Mechanistic-Empirical Calibration Process:**

  The current research provides an innovative approach to the M-E model calibration process. Moving away from traditional techniques that are based mainly on “trial and error” approaches, this research provides a methodology to fully automate the calibration process and thus provide an opportunity for pavement engineers and experts to explore the application of different optimization techniques to the M-E calibration problem, which is not possible using a traditional approach.

- **Development of a Decision-making Framework for Project Level Analysis based on Empirical and M-E Models:**

  The current research introduces a decision-making support tool at the project level of analysis. The incorporation of empirical models and M-E models in the decision-making tool allows pavement engineers and decision makers to explore different rehabilitation options based on the two model concepts. The selection of any alternative depends on the accuracy of the initial data used in developing the models.

- **Investigation of the Impact of Changing Deterioration Models at the Network Level of Analysis:**

  This research evaluates the impact of changing the deterioration models on program planning and budget analysis at the network level of analysis. It has been demonstrated that transition from empirical model-based budgets to M-E models can lead to savings, as has been shown in the presented case study. While budget savings might not always be the case, it is expected that the use of a well-calibrated M-E model will produce realistic models that truly represent the actual performance of pavement behaviour over time.

9.3 FUTURE RESEARCH

- The surface distress index (SDI) presented in this study is aggregated from various measured distresses, some of which are not currently presented in the MEPDG. Therefore, no M-E models have been developed for SDI in this study. The introduction of a new surface distress index that is aggregated from only those distresses that are present in MEPDG will facilitate the development of SDI models based on M-E concepts. A correlation between a customized SDI index based on distresses presented in MEPDG and the SDI based on all distresses would also lead to the development of SDI models based on M-E concepts.

- Correlation between the developed M-E models and existing empirical models can be developed to provide a methodology for DOT agencies to easily convert their exiting PMS models into ones based on M-E concepts.

- The current study only uses data collected for flexible pavement. Similar approaches and concepts as those adopted in this study should be expanded to include rigid pavement.

- This research attempts to use linear programming techniques and employs the genetic algorithm to determine the best M-E calibration coefficients. The automation of the calibration process presented herein provides an opportunity to employ other optimization techniques to the calibration process. In addition, the use of more site-specific data in the current GA calibration process, fine-tuning of the current GA optimization procedure (e.g., increases in the number of chromosomes or population), and investigation of other optimization techniques may produce more accurate calibration coefficients.

- The availability of more pavement condition data for other regions across Canada and North America will facilitate the further development of realistic models. In addition, the current collected data can be further broken down into different sets based on regional municipality to develop models that are more site-specific to the agency.

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Appendix I

EMPIRICAL MODELS SQL SCRIPTS FOR ROADMATRIX

INSERT INTO model_pred
(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 1, '1-Thin/Low/Strong (E)', 'NULL', 100, 99.5, 97.7, 94.9, 91.4, 87.7, 84, 80.4, 76.8, 73.5,70.3, 67.4, 64.6, 61.9, 59.4, 57.1, 54.8, 52.7, 50.8, 48.9, 47.1, 45.4, 43.8, 42.3, 40.8, 39.5, 38.1, 36.9, 35.7, 34.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, evr_code)
VALUES (10, 2, '2-Thin/Medium/Strong (E)', 'NULL', 100, 99.6, 97.8, 94.9, 91.1, 87, 82.8, 78.5, 74.4, 70.5, 66.7, 63.1, 59.6, 56.4, 53.3, 50.4, 47.6, 45, 42.5, 40.2, 37.9, 35.8, 33.8, 31.8, 30, 28.2, 26.5, 24.9, 23.3, 21.8, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 3, '3-Thin/High/Strong (E)', 'NULL', 100, 99.6, 98.2, 95.9, 92.9, 89.6, 86.2, 82.9, 79.6, 76.5, 73.5, 70.7, 68, 65.5, 63.1, 60.8, 58.7, 56.6, 54.7, 52.9, 51.1, 49.5, 47.9, 46.4, 45, 43.6, 42.3, 41, 39.8, 38.7, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24,
y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 4, '4-Thin/Low/Weak (E)', 'NULL', 98.8, 93.2, 86.7, 80.8, 75.7, 71.3, 67.5, 64.2, 61.4, 58.8, 56.6, 54.6, 52.7, 51.1, 49.6, 48.2, 46.9, 45.7, 44.6, 43.6, 42.7, 41.8, 41, 40.2, 39.4, 38.8, 38.1, 37.5, 36.9, 36.3, 1)
INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 5, '5-Thin/Medium/Weak (E)', 'NULL', 97.3, 88.7, 80.4, 73.5, 67.9, 63.2, 59.3, 56, 53.2, 50.7, 48.5, 46.5, 44.8, 43.2, 41.8, 40.5, 39.3, 38.2, 37.2, 36.3, 35.4, 34.6, 33.9, 33.2, 32.5, 31.9, 31.3, 30.8, 30.2, 29.7, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 6, '6-Thin/High/Weak (E)', 'NULL', 99.7, 96.6, 91.6, 86.1, 81, 76.3, 72.1, 68.3, 64.9, 61.8, 59.1, 56.6, 54.3, 52.2, 50.3, 48.5, 46.9, 45.4, 44, 42.7, 41.4, 40.3, 39.2, 38.2, 37.2, 36.3, 35.4, 34.6, 33.8, 33.1, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 7, '7-Medium/Low/Strong (E)', 'NULL', 100, 99.7, 98.4, 96.2, 93.4, 90.2, 87, 83.8, 80.7, 77.7, 74.8, 72, 69.5, 67, 64.7, 62.5, 60.4, 58.4, 56.6, 54.8, 53.1, 51.5, 50, 48.5, 47.1, 45.8, 44.5, 43.3, 42.1, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24
y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 8, '8-Medium/Medium/Strong (E)', 'NULL', 100, 99.8, 99, 97.5, 95.4, 92.9, 90.3, 87.6, 85, 82.4, 79.8, 77.4, 75.1, 72.8, 70.7, 68.7, 66.7, 64.9, 63.1, 61.5, 59.9, 58.3, 56.9, 55.5, 54.1, 52.8, 51.6, 50.4, 49.3, 48.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 9, '9-Medium/High/Strong (E)', 'NULL', 100, 99.5, 97.6, 94.6, 91, 87, 83, 79.1, 75.3, 71.7, 68.3, 65.1, 62, 59.2, 56.5, 53.9, 51.5, 49.2, 47.1, 45, 43.1, 41.3, 39.5,

37.8, 36.3, 34.7, 33.3, 31.9, 30.6, 29.3, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 10, '10-Medium/Low/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.7, 83.8, 79.8, 76, 72.4, 68.9, 65.6, 62.5, 59.6, 56.8, 54.2, 51.8, 49.4, 47.2, 45.1, 43.1, 41.2, 39.4, 37.7, 36, 34.5, 33, 31.5, 30.2, 28.9, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 11, '11-Medium/Medium/Weak (E)', 'NULL', 99.7, 96.7, 91.7, 86.3, 81, 76.2, 71.9, 67.9, 64.4, 61.2, 58.3, 55.7, 53.3, 51.1, 49.1, 47.2, 45.5, 43.9, 42.3, 40.9, 39.6, 38.4, 37.2, 36.1, 35.1, 34.1, 33.2, 32.3, 31.4, 30.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 12, '12-Medium/High/Weak (E)', 'NULL', 99.5, 95.5, 89.4, 83.2, 77.3, 72.1, 67.4, 63.3, 59.6, 56.3, 53.3, 50.6, 48.2, 45.9, 43.9, 42, 40.2, 38.6, 37.1, 35.7, 34.4, 33.2, 32, 31, 29.9,
29, 28.1, 27.2, 26.4, 25.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 13, '13-Thick/Low/Strong (E)', 'NULL', 100, 99.7, 98.2, 95.8, 92.8, 89.4, 85.9, 82.5, 79.2, 76, 73, 70.1, 67.4, 64.9, 62.5, 60.2, 58, 56, 54.1, 52.3, 50.6, 48.9, 47.4, 45.9, 44.5, 43.1, 41.8, 40.6, 39.4, 38.3, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (10, 14, '14-Thick/Medium/Strong (E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.5, 85.3, 82.2, 79.1, 76.1, 73.2, 70.5, 67.9, 65.4, 63.1, 60.8, 58.7, 56.7, 54.7, 52.9, 51.1, 49.5, 47.9, 46.3, 44.9, 43.5, 42.1, 40.8, 39.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 15, '15-Thick/High/Strong (E)', 'NULL', 100, 99.7, 98.5, 96.3, 93.4, 90.2, 86.8, 83.4, 80, 76.8, 73.7, 70.7, 67.8, 65.1, 62.5, 60.1, 57.8, 55.6, 53.5, 51.5, 49.6, 47.7, 46, 44.4, 42.8, 41.3, 39.8, 38.4, 37.1, 35.8, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 16, '16-Thick/Low/Weak (E)', 'NULL', 100, 99.6, 98.1, 95.5, 92.2, 88.6, 84.8, 81.1, 77.5, 74, 70.6, 67.4, 64.4, 61.6, 58.8, 56.3, 53.9, 51.6, 49.4, 47.3, 45.4, 43.5, 41.7, 40, 38.4, 36.8, 35.4, 33.9, 32.6, 31.3, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 17, '17-Thick/Medium/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.8, 83.8, 79.9, 76.1, 72.5, 69, 65.7, 62.6, 59.7, 56.9, 54.3, 51.8, 49.5, 47.3, 45.2, 43.2, 41.3, 39.5, 37.8, 36.1, 34.6, 33.1, 31.7, 30.3, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (10, 18, '18-Thick/High/Weak (E)', 'NULL', 99.9, 98.6, 95.1, 90.6, 85.7, 80.8, 76.1, 71.7, 67.6, 63.8, 60.3, 57.1, 54, 51.2, 48.6, 46.2, 43.9, 41.8, 39.8, 37.9, 36.1, 34.4, 32.8, 31.3, 29.9, 28.5, 27.2, 26, 24.8, 23.7, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,

y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 1, '1-Thin/Low/Strong (E)', 'NULL', 100, 99.5, 97.7, 94.9, 91.4, 87.7, 84, 80.4, 76.8, 73.5, 70.3, 67.4, 64.6, 61.9, 59.4, 57.1, 54.8, 52.7, 50.8, 48.9, 47.1, 45.4, 43.8, 42.3, 40.8, 39.5, 38.1, 36.9, 35.7, 34.5, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 2, '2-Thin/Medium/Strong (E)', 'NULL', 100, 99.6, 97.8, 94.9, 91.1, 87, 82.8, 78.5, 74.4, 70.5, 66.7, 63.1, 59.6, 56.4, 53.3, 50.4, 47.6, 45, 42.5, 40.2, 37.9, 35.8, 33.8, 31.8, 30, 28.2, 26.5, 24.9, 23.3, 21.8, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 3, '3-Thin/High/Strong (E)', 'NULL', 100, 99.8, 98.9, 97.3, 95.1, 92.8, 90.2, 87.7, 85.3, 82.9, 80.6, 78.4, 76.3, 74.3, 72.5, 70.7, 69, 67.4, 65.9, 64.4, 63, 61.7, 60.5, 59.3, 58.1, 57.1, 56, 55, 54, 53.1, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 4, '4-Thin/Low/Weak (E)', 'NULL', 98.8, 93.2, 86.7, 80.8, 75.7, 71.3, 67.5, 64.2, 61.4, 58.8, 56.6, 54.6, 52.7, 51.1, 49.6, 48.2, 46.9, 45.7, 44.6, 43.6, 42.7, 41.8, 41, 40.2, 39.4,
38.8, 38.1, 37.5, 36.9, 36.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 5, '5-Thin/Medium/Weak (E)', 'NULL', 97.3, 88.7, 80.4, 73.5, 67.9, 63.2, 59.3, 56, 53.2, 50.7, 48.5, 46.5, 44.8, 43.2, 41.8, 40.5, 39.3, 38.2, 37.2, 36.3, 35.4, 34.6, 33.9, 33.2, 32.5, 31.9, 31.3, 30.8, 30.2, 29.7, 1)

INSERT

```
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 6, '6-Thin/High/Weak (E)', 'NULL', 99.3, 94.8, 88.8, 83.1, 78, 73.6, 69.7, 66.4, 63.4, 60.7, 58.4, 56.3, 54.3, 52.6, 51, 49.5, 48.2, 47, 45.8, 44.7, 43.8, 42.8, 41.9, 41.1, 40.3, 39.6, 38.9, 38.3, 37.7, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 37.1, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 7, '7-Medium/Low/Strong (E)', 'NULL', 100, 99.7, 98.4, 96.2, 93.4, 90.2, 87, 83.8, 80.7, 77.7, 74.8, 72, 69.5, 67, 64.7, 62.5, 60.4, 58.4, 56.6, 54.8, 53.1, 51.5, 50, 48.5, 47.1, 45.8, 44.5, 43.3, 42.1, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 8, '8-Medium/Medium/Strong (E)', 'NULL', 100, 99.8, 98.7, 96.8, 94.4, 91.7, 88.8, 86, 83.2, 80.5, 77.9, 75.5, 73.1, 70.9, 68.8, 66.7, 64.8, 63, 61.3, 59.7, 58.1, 56.6, 55.2, 53.9, 52.6, 51.3, 50.2, 49, 47.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 46.9, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 9, '9-Medium/High/Strong (E)', 'NULL', 100, 99.5, 97.6, 94.6, 91, 87, 83, 79.1, 75.3, 71.7, 68.3, 65.1, 62, 59.2, 56.5, 53.9, 51.5, 49.2, 47.1, 45, 43.1, 41.3, 39.5, 37.8, 36.3, 34.7, 33.3, 31.9, 30.6, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 29.3, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 10, '10-Medium/Low/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.7, 83.8, 79.8, 76, 72.4, 68.9, 65.6, 62.5, 59.6, 56.8, 54.2, 51.8, 49.4, 47.2, 45.1, 43.1, 41.2, 39.4, 37.7, 36, 34.5, 33, 31.5, 30.2, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 28.9, 1)
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INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 11, '11-Medium/Medium/Weak (E)', 'NULL', 99.7, 96.7, 91.7, 86.3, 81, 76.2, 71.9, 67.9, 64.4, 61.2, 58.3, 55.7, 53.3, 51.1, 49.1, 47.2, 45.5, 43.9, 42.3, 40.9, 39.6, 38.4, 37.2, 36.1, 35.1, 34.1, 33.2, 32.3, 31.4, 30.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 12, '12-Medium/High/Weak (E)', 'NULL', 99.5, 95.5, 89.4, 83.2, 77.3, 72.1, 67.4, 63.3, 59.6, 56.3, 53.3, 50.6, 48.2, 45.9, 43.9, 42, 40.2, 38.6, 37.1, 35.7, 34.4, 33.2, 32, 31, 29.9, 29, 28.1, 27.2, 26.4, 25.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 13, '13-Thick/Low/Strong (E)', 'NULL', 100, 99.9, 99.5, 98.4, 96.9, 95.1, 93, 90.8, 88.6, 86.3, 84.1, 82, 79.9, 77.9, 75.9, 74, 72.2, 70.5, 68.9, 67.3, 65.8, 64.3, 62.9, 61.5, 60.2, 59, 57.8, 56.6, 55.5, 54.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 14, '14-Thick/Medium/Strong (E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.5, 85.3, 82.2, 79.1, 76.1, 73.2, 70.5, 67.9, 65.4, 63.1, 60.8, 58.7, 56.7, 54.7, 52.9, 51.1, 49.5, 47.9, 46.3, 44.9, 43.5, 42.1, 40.8, 39.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 15, '15-Thick/High/Strong (E)', 'NULL', 100, 99.7, 98.5, 96.3, 93.4, 90.2, 86.8, 83.4, 80, 76.8, 73.7, 70.7, 67.8, 65.1, 62.5, 60.1, 57.8, 55.6, 53.5, 51.5, 49.6, 47.7,

46, 44.4, 42.8, 41.3, 39.8, 38.4, 37.1, 35.8, 1)

```
        INSERT
        INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 16, '16-Thick/Low/Weak (E)', 'NULL', 100, 99.6, 98.1, 95.5, 92.2, 88.6, 84.8, 81.1, 77.5, 74, 70.6, 67.4, 64.4, 61.6, 58.8, 56.3, 53.9, 51.6, 49.4, 47.3, 45.4, 43.5, 41.7, 40, 38.4, 36.8, 35.4, 33.9, 32.6, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 31.3, 1)
        INSERT
        INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 17, '17-Thick/Medium/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.8, 83.8, 79.9, 76.1, 72.5, 69, 65.7, 62.6, 59.7, 56.9, 54.3, 51.8, 49.5, 47.3, 45.2, 43.2, 41.3, 39.5, 37.8, 36.1, 34.6, 33.1, 31.7, 30.3, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 1)
        INSERT
        INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (11, 18, '18-Thick/High/Weak (E)', 'NULL', 99.9, 98.6, 95.1, 90.6, 85.7, 80.8, 76.1, 71.7, 67.6, 63.8, 60.3, 57.1, 54, 51.2, 48.6, 46.2, 43.9, 41.8, 39.8, 37.9, 36.1, 34.4, 32.8, 31.3, 29.9, 28.5, 27.2, 26, 24.8, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 1)
        INSERT
        INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 1, '1-Thin/Low/Strong (E)', 'NULL', 100, 99.5, 97.7, 94.9, 91.4, 87.7, 84, 80.4, 76.8, 73.5, 70.3, 67.4, 64.6, 61.9, 59.4, 57.1, 54.8, 52.7, 50.8, 48.9, 47.1, 45.4, 43.8, 42.3, 40.8, 39.5, 38.1, 36.9, 35.7, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 34.5, 1)
        INSERT
        INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
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VALUES (12, 2, '2-Thin/Medium/Strong (E)', 'NULL', 100, 99.6, 97.8, 94.9, 91.1, 87, 82.8, 78.5, 74.4, 70.5, 66.7, 63.1, 59.6, 56.4, 53.3, 50.4, 47.6, 45, 42.5, 40.2, 37.9, 35.8, 33.8, 31.8, 30, 28.2, 26.5, 24.9, 23.3, 21.8, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (12, 3, '3-Thin/High/Strong (E)', 'NULL', 100, 99.6, 98.3, 96, 93.2, 90, 86.8, 83.7, 80.6, 77.7, 74.9, 72.2, 69.7, 67.3, 65.1, 62.9, 60.9, 59, 57.2, 55.5, 53.9, 52.3, 50.8, 49.4, 48.1, 46.8, 45.6, 44.4, 43.3, 42.2, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (12, 4, '4-Thin/Low/Weak (E)', 'NULL', 98.8, 93.2, 86.7, 80.8, 75.7, 71.3, 67.5, 64.2, 61.4, 58.8, 56.6, 54.6, 52.7, 51.1, 49.6, 48.2, 46.9, 45.7, 44.6, 43.6, 42.7, 41.8, 41, 40.2, 39.4, 38.8, 38.1, 37.5, 36.9, 36.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (12, 5, '5-Thin/Medium/Weak (E)', 'NULL', 97.3, 88.7, 80.4, 73.5, 67.9, 63.2, 59.3, 56, 53.2, 50.7, 48.5, 46.5, 44.8, 43.2, 41.8, 40.5, 39.3, 38.2, 37.2, 36.3, 35.4, 34.6, 33.9, 33.2, 32.5, 31.9, 31.3, 30.8, 30.2, 29.7, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (12, 6, '6-Thin/High/Weak (E)', 'NULL', 99, 94, 87.8, 82.1, 77.1, 72.8, 69, 65.7, 62.8, 60.3, 58, 55.9, 54.1, 52.4, 50.9, 49.5, 48.2, 47, 45.8, 44.8, 43.8, 42.9, 42.1, 41.3, 40.5, 39.8, 39.1, 38.5, 37.9, 37.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,

y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 7, '7-Medium/Low/Strong (E)', 'NULL', 100, 99.7, 98.4, 96.2, 93.4, 90.2, 87, 83.8, 80.7, 77.7, 74.8, 72, 69.5, 67, 64.7, 62.5, 60.4, 58.4, 56.6, 54.8, 53.1, 51.5, 50, 48.5, 47.1, 45.8, 44.5, 43.3, 42.1, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 41, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 8, '8-Medium/Medium/Strong (E)', 'NULL', 100, 99.7, 98.4, 96.3, 93.6, 90.7, 87.7, 84.7, 81.7, 78.9, 76.2, 73.7, 71.3, 69, 66.8, 64.8, 62.8, 61, 59.2, 57.6, 56, 54.5, 53.1, 51.7, 50.4, 49.2, 48, 46.8, 45.8, 44.7, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 9, '9-Medium/High/Strong (E)', 'NULL', 100, 99.5, 97.6, 94.6, 91, 87, 83, 79.1, 75.3, 71.7, 68.3, 65.1, 62, 59.2, 56.5, 53.9, 51.5, 49.2, 47.1, 45, 43.1, 41.3, 39.5, 37.8, 36.3, 34.7, 33.3, 31.9, 30.6, 29.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 10, '10-Medium/Low/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.7, 83.8, 79.8, 76, 72.4, 68.9, 65.6, 62.5, 59.6, 56.8, 54.2, 51.8, 49.4, 47.2, 45.1, 43.1, 41.2, 39.4, 37.7, 36, 34.5, 33, 31.5, 30.2, 28.9, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 11, '11-Medium/Medium/Weak (E)', 'NULL', 99.7, 96.7, 91.7, 86.3, 81, 76.2, 71.9, 67.9, 64.4, 61.2, 58.3, 55.7, 53.3, 51.1, 49.1, 47.2, 45.5, 43.9, 42.3, 40.9, 39.6, 38.4, 37.2, 36.1, 35.1, 34.1, 33.2, 32.3, 31.4, 30.6, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 12, '12-Medium/High/Weak (E)', 'NULL', 99.5, 95.5, 89.4, 83.2, 77.3, 72.1, 67.4, 63.3, 59.6, 56.3, 53.3, 50.6, 48.2, 45.9, 43.9, 42, 40.2, 38.6, 37.1, 35.7, 34.4, 33.2, 32, 31, 29.9, 29, 28.1, 27.2, 26.4, 25.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 13, '13-Thick/Low/Strong (E)', 'NULL', 100, 99.9, 99.4, 98.2, 96.6, 94.7, 92.5, 90.2, 87.9, 85.6, 83.4, 81.2, 79.1, 77.1, 75.1, 73.3, 71.5, 69.8, 68.1, 66.5, 65, 63.6, 62.2, 60.9, 59.6, 58.3, 57.2, 56, 54.9, 53.9, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 14, '14-Thick/Medium/Strong (E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.5, 85.3, 82.2, 79.1, 76.1, 73.2, 70.5, 67.9, 65.4, 63.1, 60.8, 58.7, 56.7, 54.7, 52.9, 51.1, 49.5, 47.9, 46.3, 44.9, 43.5, 42.1, 40.8, 39.6, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 15, '15-Thick/High/Strong (E)', 'NULL', 100, 99.7, 98.5, 96.3, 93.4, 90.2, 86.8, 83.4, 80, 76.8, 73.7, 70.7, 67.8, 65.1, 62.5, 60.1, 57.8, 55.6, 53.5, 51.5, 49.6, 47.7, 46, 44.4, 42.8, 41.3, 39.8, 38.4, 37.1, 35.8, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 16, '16-Thick/Low/Weak (E)', 'NULL', 100, 99.6, 98.1, 95.5, 92.2, 88.6, 84.8, 81.1, 77.5, 74, 70.6, 67.4, 64.4, 61.6, 58.8, 56.3, 53.9, 51.6, 49.4, 47.3, 45.4, 43.5, 41.7, 40, 38.4, 36.8, 35.4, 33.9, 32.6, 31.3, 1)

```
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 17, '17-Thick/Medium/Weak (E)', 'NULL', 100, 99.6, 97.9, 95.1, 91.6, 87.8, 83.8, 79.9, 76.1, 72.5, 69, 65.7, 62.6, 59.7, 56.9, 54.3, 51.8, 49.5, 47.3, 45.2, 43.2, 41.3, 39.5, 37.8, 36.1, 34.6, 33.1, 31.7, 30.3, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 29, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (12, 18, '18-Thick/High/Weak (E)', 'NULL', 99.9, 98.6, 95.1, 90.6, 85.7, 80.8, 76.1, 71.7, 67.6, 63.8, 60.3, 57.1, 54, 51.2, 48.6, 46.2, 43.9, 41.8, 39.8, 37.9, 36.1, 34.4, 32.8, 31.3, 29.9, 28.5, 27.2, 26, 24.8, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 23.7, 1)
```

MECHNISTIC-EMPIRICAL MODELS SQL SCRIPTS FOR ROADMATRIX

INSERT INTO model_pred
(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 1, '1-Thin/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.2, 97.8, 95.8, 93.5, 91, 88.3, 85.6, 83, 80.4, 77.8, 75.3, 73, 70.7, 68.5, 66.3, 64.3, 62.3, 60.5, 58.7, 56.9, 55.3, 53.7, 52.1, 50.7, 49.2, 47.9, 46.5, 45.3, 1)

INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 2, '2-Thin/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 1)

INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 3, '3-Thin/High/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 1)

INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 4, '4-Thin/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 1)

INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (13, 5, '5-Thin/Medium/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6, 73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4, 38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (13, 6, '6-Thin/High/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6, 73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4, 38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (13, 7, '7-Medium/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.4, 98.3, 96.7, 94.7, 92.6, 90.4, 88.1, 85.9, 83.6, 81.5, 79.4, 77.4, 75.5, 73.6, 71.9, 70.1, 68.5, 66.9, 65.4, 64, 62.6, 61.3, 60, 58.8, 57.6, 56.5, 55.4, 54.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (13, 8, '8-Medium/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (13, 9, '9-Medium/High/Strong (M-E)', 'NULL', 100, 99.6, 98, 95.2, 91.8, 88, 84.1, 80.3, 76.5, 72.9, 69.4, 66.1, 63, 60, 57.2, 54.6, 52, 49.6, 47.4, 45.2, 43.2, 41.2, 39.4, 37.6, 35.9, 34.3, 32.7, 31.2, 29.8, 28.4, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,

y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 10, '10-Medium/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 11, '11-Medium/Medium/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 12, '12-Medium/High/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 13, '13-Thick/Low/Strong (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 14, '14-Thick/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.7, 96.9, 94.6, 92.1, 89.5, 87, 84.5, 82.1, 79.9, 77.7, 75.7, 73.7, 71.9, 70.2, 68.6, 67, 65.6, 64.2, 62.9, 61.6, 60.4, 59.3, 58.2, 57.2, 56.2, 55.3, 54.4, 53.5, 1)
INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 15, '15-Thick/High/Strong (M-E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.3, 85, 81.7, 78.5, 75.3, 72.3, 69.3, 66.5, 63.8, 61.2, 58.8, 56.4, 54.2, 52, 50, 48, 46.2, 44.4, 42.6, 41, 39.4, 37.9, 36.4, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 16, '16-Thick/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.4, 93.8, 91, 88, 85.2, 82.4, 79.7, 77.2, 74.7, 72.5, 70.3, 68.3, 66.4, 64.6, 62.8, 61.2, 59.7, 58.2, 56.8, 55.5, 54.3, 53.1, 51.9, 50.8, 49.8, 48.8, 47.8, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 17, '17-Thick/Medium/Weak (M-E)', 'NULL', 100, 99.6, 98.3, 96, 93.2, 90.1, 86.9, 83.8, 80.7, 77.8, 75, 72.4, 70, 67.6, 65.4, 63.3, 61.4, 59.5, 57.8, 56.1, 54.5, 53, 51.6, 50.2, 48.9, 47.7, 46.5, 45.3, 44.3, 43.2, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (13, 18, '18-Thick/High/Weak (M-E)', 'NULL', 100, 99.2, 96.7, 92.9, 88.4, 83.6, 78.9, 74.4, 70.1, 66, 62.2, 58.6, 55.2, 52.1, 49.1, 46.4, 43.7, 41.3, 39, 36.8, 34.7, 32.8, 30.9, 29.1, 27.5, 25.9, 24.3, 22.9, 21.5, 20.2, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 1, '1-Thin/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.2, 97.8, 95.8, 93.5, 91, 88.3, 85.6, 83, 80.4, 77.8, 75.3, 73, 70.7, 68.5, 66.3, 64.3, 62.3, 60.5, 58.7, 56.9, 55.3, 53.7, 52.1, 50.7, 49.2, 47.9, 46.5, 45.3, 1)

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INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 2, '2-Thin/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 3, '3-Thin/High/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 4, '4-Thin/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 5, '5-Thin/Medium/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6, 73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4, 38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 6, '6-Thin/High/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6, 73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4,
```

38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (14, 7, '7-Medium/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.4, 98.3, 96.7, 94.7, 92.6, 90.4, 88.1, 85.9, 83.6, 81.5, 79.4, 77.4, 75.5, 73.6, 71.9, 70.1, 68.5, 66.9, 65.4, 64, 62.6, 61.3, 60, 58.8, 57.6, 56.5, 55.4, 54.3, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (14, 8, '8-Medium/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (14, 9, '9-Medium/High/Strong (M-E)', 'NULL', 100, 99.6, 98, 95.2, 91.8, 88, 84.1, 80.3, 76.5, 72.9, 69.4, 66.1, 63, 60, 57.2, 54.6, 52, 49.6, 47.4, 45.2, 43.2, 41.2, 39.4, 37.6, 35.9, 34.3, 32.7, 31.2, 29.8, 28.4, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (14, 10, '10-Medium/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (14, 11, '11-Medium/Medium/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 12, '12-Medium/High/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 13, '13-Thick/Low/Strong (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 14, '14-Thick/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.7, 96.9, 94.6, 92.1, 89.5, 87, 84.5, 82.1, 79.9, 77.7, 75.7, 73.7, 71.9, 70.2, 68.6, 67, 65.6, 64.2, 62.9, 61.6, 60.4, 59.3, 58.2, 57.2, 56.2, 55.3, 54.4, 53.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 15, '15-Thick/High/Strong (M-E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.3, 85, 81.7, 78.5, 75.3, 72.3, 69.3, 66.5, 63.8, 61.2, 58.8, 56.4, 54.2, 52, 50, 48, 46.2, 44.4, 42.6, 41, 39.4, 37.9, 36.4, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24,

y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 16, '16-Thick/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.4, 93.8, 91, 88, 85.2, 82.4, 79.7, 77.2, 74.7, 72.5, 70.3, 68.3, 66.4, 64.6, 62.8, 61.2, 59.7, 58.2, 56.8, 55.5, 54.3, 53.1, 51.9, 50.8, 49.8, 48.8, 47.8, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 17, '17-Thick/Medium/Weak (M-E)', 'NULL', 100, 99.6, 98.3, 96, 93.2, 90.1, 86.9, 83.8, 80.7, 77.8, 75, 72.4, 70, 67.6, 65.4, 63.3, 61.4, 59.5, 57.8, 56.1, 54.5, 53, 51.6, 50.2, 48.9, 47.7, 46.5, 45.3, 44.3, 43.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (14, 18, '18-Thick/High/Weak (M-E)', 'NULL', 100, 99.2, 96.7, 92.9, 88.4, 83.6, 78.9, 74.4, 70.1, 66, 62.2, 58.6, 55.2, 52.1, 49.1, 46.4, 43.7, 41.3, 39, 36.8, 34.7, 32.8, 30.9, 29.1, 27.5, 25.9, 24.3, 22.9, 21.5, 20.2, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 1, '1-Thin/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.2, 97.8, 95.8, 93.5, 91, 88.3, 85.6, 83, 80.4, 77.8, 75.3, 73, 70.7, 68.5, 66.3, 64.3, 62.3, 60.5, 58.7, 56.9, 55.3, 53.7, 52.1, 50.7, 49.2, 47.9, 46.5, 45.3, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 2, '2-Thin/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6, 83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8, 46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 1)
INSERT

```
            INTO      model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04,
y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,
y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40,
y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 3, '3-Thin/High/Strong (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6,
83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8,
46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2,
38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 1)
            INSERT
            INTO      model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04,
y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,
y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40,
y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 4, '4-Thin/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.3, 96, 93.2, 90, 86.6,
83.3, 80.1, 77, 74, 71.1, 68.4, 65.8, 63.4, 61.1, 58.9, 56.8, 54.8, 53, 51.2, 49.5, 47.8,
46.3, 44.8, 43.4, 42, 40.7, 39.4, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2,
38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 38.2, 1)
            INSERT
            INTO      model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04,
y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,
y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40,
y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 5, '5-Thin/Medium/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6,
73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4,
38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5,
31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 1)
            INSERT
            INTO      model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04,
y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,
y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40,
y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 6, '6-Thin/High/Weak (M-E)', 'NULL', 99.8, 97.3, 92.6, 87.4, 82.4, 77.6,
73.3, 69.4, 65.9, 62.7, 59.7, 57.1, 54.6, 52.4, 50.3, 48.4, 46.7, 45, 43.5, 42, 40.7, 39.4,
38.2, 37.1, 36.1, 35, 34.1, 33.2, 32.3, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5,
31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 31.5, 1)
            INSERT
            INTO      model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04,
y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22,
y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40,
y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 7, '7-Medium/Low/Strong (M-E)', 'NULL', 100, 99.9, 99.4, 98.3, 96.7, 94.7,
92.6, 90.4, 88.1, 85.9, 83.6, 81.5, 79.4, 77.4, 75.5, 73.6, 71.9, 70.1, 68.5, 66.9, 65.4, 64,
62.6, 61.3, 60, 58.8, 57.6, 56.5, 55.4, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3,
54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 54.3, 1)
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INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 8, '8-Medium/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 9, '9-Medium/High/Strong (M-E)', 'NULL', 100, 99.6, 98, 95.2, 91.8, 88, 84.1, 80.3, 76.5, 72.9, 69.4, 66.1, 63, 60, 57.2, 54.6, 52, 49.6, 47.4, 45.2, 43.2, 41.2, 39.4, 37.6, 35.9, 34.3, 32.7, 31.2, 29.8, 28.4, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 10, '10-Medium/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.5, 94.1, 91.3, 88.6, 85.8, 83.1, 80.6, 78.1, 75.8, 73.6, 71.6, 69.6, 67.8, 66.1, 64.4, 62.9, 61.4, 60, 58.7, 57.4, 56.2, 55, 53.9, 52.9, 51.9, 50.9, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 50, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 11, '11-Medium/Medium/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 12, '12-Medium/High/Weak (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9,

60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 13, '13-Thick/Low/Strong (M-E)', 'NULL', 100, 99.7, 98.6, 96.7, 94.3, 91.8, 89.1, 86.5, 83.9, 81.5, 79.2, 77, 74.9, 73, 71.1, 69.4, 67.7, 66.2, 64.7, 63.3, 61.9, 60.7, 59.5, 58.3, 57.2, 56.2, 55.2, 54.2, 53.3, 52.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 14, '14-Thick/Medium/Strong (M-E)', 'NULL', 100, 99.7, 98.7, 96.9, 94.6, 92.1, 89.5, 87, 84.5, 82.1, 79.9, 77.7, 75.7, 73.7, 71.9, 70.2, 68.6, 67, 65.6, 64.2, 62.9, 61.6, 60.4, 59.3, 58.2, 57.2, 56.2, 55.3, 54.4, 53.5, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 15, '15-Thick/High/Strong (M-E)', 'NULL', 100, 99.8, 98.9, 97.1, 94.5, 91.6, 88.3, 85, 81.7, 78.5, 75.3, 72.3, 69.3, 66.5, 63.8, 61.2, 58.8, 56.4, 54.2, 52, 50, 48, 46.2, 44.4, 42.6, 41, 39.4, 37.9, 36.4, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)
VALUES (15, 16, '16-Thick/Low/Weak (M-E)', 'NULL', 100, 99.7, 98.5, 96.4, 93.8, 91, 88, 85.2, 82.4, 79.7, 77.2, 74.7, 72.5, 70.3, 68.3, 66.4, 64.6, 62.8, 61.2, 59.7, 58.2, 56.8, 55.5, 54.3, 53.1, 51.9, 50.8, 49.8, 48.8, 47.8, 1)
INSERT
INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (15, 17, '17-Thick/Medium/Weak (M-E)', 'NULL', 100, 99.6, 98.3, 96, 93.2, 90.1, 86.9, 83.8, 80.7, 77.8, 75, 72.4, 70, 67.6, 65.4, 63.3, 61.4, 59.5, 57.8, 56.1, 54.5, 53, 51.6, 50.2, 48.9, 47.7, 46.5, 45.3, 44.3, 43.2, 1)

INSERT

INTO model_pred(pave_code, crvno, fdesc, notes, y01, y02, y03, y04, y05, y06, y07, y08, y09, y10, y11, y12, y13, y14, y15, y16, y17, y18, y19, y20, y21, y22, y23, y24, y25, y26, y27, y28, y29, y30, y31, y32, y33, y34, y35, y36, y37, y38, y39, y40, y41, y42, y43, y44, y45, y46, y47, y48, y49, y50, envr_code)

VALUES (15, 18, '18-Thick/High/Weak (M-E)', 'NULL', 100, 99.2, 96.7, 92.9, 88.4, 83.6, 78.9, 74.4, 70.1, 66, 62.2, 58.6, 55.2, 52.1, 49.1, 46.4, 43.7, 41.3, 39, 36.8, 34.7, 32.8, 30.9, 29.1, 27.5, 25.9, 24.3, 22.9, 21.5, 20.2, 1)