Developing Cost-Effective Pavement Maintenance and Rehabilitation Schedules: Application of MEPDG-Based Distress Models and Key Performance Index

by

Gulfam Jannat

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Civil Engineering

Waterloo, Ontario, Canada, 2017

Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	NAME: Judy Corley-Lay Title: Dr. North Carolina Department of Transportation (Rtd)
Supervisor(s)	NAME: Susan L. Tighe Title: Professor, Civil & Environmental Engineering
Internal Member	NAME: Giovanni Cascante Title: Professor, Civil & Environmental Engineering
Internal-external Member	NAME: Alexander Penlidis Title: Professor, Chemical Engineering
Other Member(s)	NAME: Ningyuan Li Title: Dr., Ministry of Transportation Ontario

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. I understand that my thesis may be made available electronically to the public.

Abstract

Pavement Maintenance and Rehabilitation (M&R) are the most critical and expensive components of infrastructure asset management. Increasing traffic load, climate change and resource limitations for road maintenance accelerate pavement deterioration and eventually increase the need for future maintenance treatments. Consequently, pavement management programs are increasingly complex. The complexities are attributed to the precise assessment process of the overall pavement condition, realistic distress prediction and identification of cost-effective M&R schedules. Cost-effective road M&R practices are only possible when the evaluation of pavement condition is precise, pavement deterioration models are accurate, and resources must also be available at the right time.

In a Pavement Management System (PMS), feasible M&R treatments are identified at the end of each branch of the decision trees. The decision trees are based on empirical relationships of the pavement performance index. Moreover, the predicted improvements in pavement performance for any treatment are set based on engineering experiences. Furthermore, the remaining service life of the pavement is estimated from the predicted deterioration of the overall condition. The future deterioration of the overall condition is estimated based on the initial condition and by considering only the effect of age notwithstanding the effect of traffic or materials. In assessing the overall condition of the pavement, this research overcomes the limitations of engineering judgment by incorporating a Mechanistic-Empirical (M-E) approach and estimating the improvement in performance for specific treatment types. It also considers the effect of traffic and materials on pavement performance to precisely predict its future deterioration and subsequent remaining service life.

The objective of this research is to develop cost-effective pavement M&R schedules by incorporating (a) the M-E approach into the overall condition index and (b) the estimate of performance indices by considering the factors affecting pavement performance. The research objective will be accomplished by (i) incorporating variability analysis of existing performance evaluation practices and maintenance decisions of pavement, (ii) investigating estimates of existing performance indices, (iii) incorporating the M-E approach: sensitivity analysis, prediction, comparison and verification, (iv) estimating the deterioration model based on traffic characteristics and material types, and (v) identifying cost-effective M&R treatment options through Life Cycle Cost Analysis (LCCA). This study uses the pavement performance data of Ontario highways recorded in the Ministry of Transportation (MTO) pavement database.

Precise assessment of pavement condition is a significant part in achieving the research goal. In a PMS, an accurate location reference system is necessary for managing pavement evaluations and maintenance. The length of the pavement section selected for evaluation may have a significant impact on the assessment irrespective of the type of performance indices. In Ontario, the highway section lengths range from 50m to 50,000m. For this reason, a variability in performance evaluation is investigated due to changes in section length. This study considers rut depth, Pavement Condition Index (PCI), and International Roughness Index (IRI) as performance indices. The distributions of these indices are compared by the following groupings of section lengths: 50m, 500m, 1,000m and 10,000m. The variations of performance

assessments due to changing section lengths are investigated based on their impact on maintenance decisions. A Monte Carlo simulation is carried out by varying section lengths to estimate probabilities of maintenance work requirements. Results of such empirical investigations reveal that most of the longer sections are evaluated with low rut depth and the shorter sections are evaluated with high rut depth. This Monte Carlo simulation also reveals that 50m sections have a higher probability of maintenance requirements than 500m sections.

The method of estimating performance indices is also investigated to identify the requirement of improvement in estimation of the prediction models. Generally, in a PMS, the prediction models of Key Performance Indicators (KPIs) are estimated by using the Ordinary Least Square (OLS) approach. However, the OLS approach can be inefficient if unobserved factors influencing individual KPIs are correlated with each other. For this reason, regression models for KPI predictions are estimated by using an approach called the ‘Seemingly Unrelated Regression (SUR)' method.

The M-E approach is used in this study to predict the future distresses by employing mechanistic-empirical models to analyze the impact of traffic, climate, materials and pavement structure. The Mechanistic-Empirical Pavement Design Guide (MEPDG) software uses a three-level hierarchical input to predict performance in terms of IRI, permanent deformation (rut depth), total cracking (reflective and alligator), asphalt concrete (AC) thermal fracture, AC bottom-up fatigue cracking and AC top-down fatigue cracking. However, these inputs have different levels of accuracy, which may have a significant impact on performance prediction. It would be ineffective to put effort for obtaining accuracy at Level 1 for all inputs. For this reason, a sensitivity analysis is carried out based on an experimental design to identify the effect of the accuracy level of inputs on the distresses. Following this, a local sensitivity analysis is carried out to identify the main effect of input variables. Interaction effects are also analyzed based on a random combination of the inputs.

Since the deterioration of pavement is affected by site-specific traffic, local climate and properties of materials, these variables are carefully considered during the development of the pavement deterioration model to assess overall pavement conditions. The prediction model is developed by using a regression approach considering distresses of the M-E approach. In this study, the deterioration model is estimated for three groups of Annual Average Daily Traffic (AADT) to recognize their individual impact along with properties of materials. The time required for maintenance is also estimated for these categories. The investigations reveal that the expected time to maintenance for overlay with Dense Friction Course (DFC) and Superpave mixes is higher than other Hot Laid (HL) asphalt layers. This will help pavement designers and managers to make informed decisions. The probability of failure is also investigated by a probabilistic approach.

With the increasing trend towards M&R of existing pavements, it is essential to make cost-effective use of the M&R budget. As such, identification of associated cost-effective M&R treatments is not always simple in most PMS. For this reason, a LCCA is carried out for alternate pavement treatments using the deterioration model based on traffic levels and material types. Comparing the Net Present Worth (NPW) value of alternative treatment options reveals that the overlay of pavement with DFC is the most cost-effective choice in the case of higher AADT. On the other hand, overlay with Hot Laid-1 (HL-1) is a cost-effective treatment option for highway sections with lower AADT.

Although the results are related to the Ontario highway system, this can also be applied elsewhere with similar conditions. The outcome of the empirical investigations will result in the adoption of efficient road M&R programs for highways based on realistic performance predictions, which have significant impact on infrastructure asset management.

Acknowledgements

The author wishes to express her sincerest gratitude to Professor Susan L. Tighe for her continuous guidance and encouragement. Throughout the whole study, she extended her experienced views and understanding of the problem of research.

She not only supervised the research, but always remained supportive with matters relating to the author's academic and personal life like her mother. She was unreservedly encouraging and helped the author maintain focus on her future goals at all times. Through her own personal stories, Professor Tighe inspired confidence in the face of any challenges related to the problem of research. Her outstanding way of supervising this research work, her guidance and her unparalleled support throughout this study is greatly appreciated.

The support from the Ministry of Transportation Ontario (MTO) is gratefully acknowledged. The author would like to acknowledge the help of Dr. Li Ningyuan (Senior Pavement Management Engineer, Pavements and Foundations Section, MTO) and Mr. Warren Lee, (Pavement Design Engineer, Pavement and Foundation Section, MTO) during this research work.

The individual efforts of all colleagues at the Centre for Pavement and Transportation Technology (CPATT) in this study are also acknowledged.

The author also would like to express her heartfelt thanks to her husband, Professor Khandker Nurul Habib (University of Toronto), her father, Advocate Mujibur Rahman (Bangladesh Supreme Court), her mother, Mahmuda Khatun (ex-teacher, Bindubashini Government Girls' High School), her father-in law, Rajjak Khandker, her brothers, Colonel Imrul Kais, Imtiaz Kais, Irfan Qais, Imdadul Kais and Imran Kais and all other members of her family for providing the support to complete this study.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AADT	Annual Average Daily Traffic
AADTT	Annual Average Daily Truck Traffic
AASHO	American Association of State Highways Officials
AASHTO	American Association of State Highway and Transportation Officials
AC	Asphalt Concrete
CalM-E	California Mechanistic-Empirical
CBR	California Bearing Ratio
C-LTPP	Canadian Long Term Pavement Performance
DFC	Dense Friction Course
DMI	Distress Manifestation Index
EDC	Environmental Damage Cost
ESAL	Equivalent Single Axle Load
GLS	Generalized Least Squares
GP	Gaussian Process
HL	Hot Laid
HMA	Hot-Mix Asphalt
HPMA	Highway Pavement Management Application
HRB	Highway Research Board
IRI	International Roughness Index
JPCP	Jointed Plain Concrete Pavement
KPI	Key Performance Indicators
LCA	Life Cycle Assessment
LCCA	Life Cycle Cost Analysis
LTPP	Long Term Pavement Performance
M&R	Maintenance and Rehabilitation

M-E	Mechanistic-Empirical
MEPDG	Mechanistic-Empirical Pavement Design Guide
MnRoad	Minnesota Road Research Project
MTO	Ministry of Transportation Ontario
NCHRP	National Cooperative Highway Research Program
NPW	Net Present Worth
OLS	Ordinary Least Square
OPSS	Ontario Provincial Standard Specification
PADMG	Pavement Asset Design and Management Guide
PCI	Pavement Condition Index
PG	Performance Grade
PMS	Pavement Management Systems
PR	Public Roads
RBD	Randomized Block Design
RCI	Riding Comfort Index
RCR	Riding Comfort Rating
RI	Rutting Index
SAI	Structural Adequacy Index
SUR	Seemingly Unrelated Regression
TAC	Transportation Association of Canada
TTC	Truck Traffic Class

CHAPTER 1
INTRODUCTION

1.1 Background

The majority of highway agencies in the United States used their resources for the construction of new pavement networks from 1950 until the late 1980s (Dornan 2002). In the 1990s, many departments of transportation recognized the importance of maintenance. With the majority of the U.S. interstate system built in the 1980s, the emphasis gradually shifted toward rehabilitation activities during this time (NCHRP 2004). In recent years, increased emphasis has been placed on pavement preservation and preventive maintenance concepts and programs. The American Society of Civil Engineers (ASCE) graded the U.S. pavement infrastructure as the top infrastructure concern and estimated a cost of $91 billion to maintain the pavements, with a shortfall of $89 billion annually (ASCE 2013). In Canada, as noted in the Transportation Association of Canada (TAC) Pavement Asset Design and Management Guide (PADMG), the situation is similar (TAC 2013).

Canada has a vast network of 900,000km two-lane public roads and the national highway system is composed of over 38,000km of important national and provincial highways. This road system alone has an asset value of approximately $160 billion (TAC 2013). Canada's economy is dependent on good pavement infrastructure as 90% of all goods and services are transported via trucks (TAC 2013). Since truck transportation of goods is prominent in Canada, this has a large impact on the performance of the nation's pavement. In Ontario, the Ministry of Transportation Ontario (MTO) invests approximately $200 million annually to ensure that the Ontario highway network is maintained above the levels of serviceability required for each classified highway (Ningyuan 2004). Thus, a cost-effective pavement M&R approach is required to allocate the limited budget. Selection of appropriate M&R strategies is a key aspect of the pavement management process. For these reasons, an M&R framework based on accurate and realistic predictions of pavement distress and associated M&R treatment costs is required.

As per TAC (2013), "The basic purpose of Pavement Management Systems (PMS) is to achieve the best value possible for the available public funds and to provide safe, comfortable and economic transportation." An effective PMS is only possible when accurate pavement performance prediction models are available. In PMS, Key Performance Indicators (KPIs) are used for predicting the overall condition of the pavement. Overall condition of pavement predicted by these KPIs is used for estimating future needs and cost effectiveness of M&R activities.

In Ontario, the KPI models are developed from road condition surveys for selected distresses. These models were initially developed based on the weighting distresses that are evaluated or rated in a subjective manner. These weights are assigned by the MTO to 15 distress categories, which are dependent on the highway type (MTO 2007). MTO has also recently adapted semi-automated measurement to provide improved measurement and consistency (Ningyuan 2013). For highway systems in Ontario, the Pavement Condition Index (PCI) is used generally as an overall condition index in the maintenance decision-making process (MTO 1990). Similarly, in any PMS, the M&R strategies are selected based on the condition of the pavement performance index. Through precise estimates, appropriate performance indices can help ensure reasonable predictions of the overall pavement condition. Precise evaluations or predictions can help to ensure maximized pavement performance through the application of the correct treatment applied at the right time during the pavement life cycle. Thus, precise evaluation or prediction of performance using appropriate KPIs can improve the current PMS practices.

1.2 Problem Statement

Every year different transportation agencies spend billions of dollars on infrastructure asset management. Highway agencies are currently grappling with the identification and implementation of cost-effective practices to preserve the huge investment made in the highway infrastructure. Rapidly increasing traffic, climate change and resource limitations for road maintenance accelerate pavement deterioration. Thus, predicting realistic distress and identifying subsequent cost-effective M&R schedules are becoming progressively more complex.

Transportation agencies are facing difficulties regarding the accuracy and efficiency of prediction and evaluation processes for overall pavement conditions. Development of a comprehensive and accurate model of KPIs to predict overall pavement conditions from specific distresses and cracking is a constant challenge in pavement engineering (Haas 1994).

The PCI is typically used as the primary index in the pavement M&R decision trees. These decision trees use a series of tests to capture the decision-making process in selecting appropriate M&R treatments based on the status of KPIs, including pavement roughness, rutting and individual distresses. The feasible M&R treatments are identified at the end of each branch. These decision trees are based on the empirical relationships of KPIs. Moreover, the predicted improvement in performance, in terms of the indices after treatment, are set based on engineering experiences. Furthermore, the remaining service life of pavement is estimated from the predicted deterioration of the overall condition. The future deterioration of the overall pavement condition is estimated based on the initial condition by considering only the effect of age notwithstanding the effect of traffic or materials (Kazmierowski 2001). However, the improvement in performance will not be similar for different material types. Moreover, the deterioration of the pavement condition over time will not be similar for different traffic levels and material types.

The performance predictions that consider engineering judgement or historical records can be misleading to the pavement engineers and managers identifying the appropriate treatment and time for pavement maintenance. Therefore, there is a gap in the precise prediction of pavement service life by assessing the overall condition and how prediction models are used in M&R strategy in the PMS.

1.3 Research Hypothesis

It is observed that the result of a PMS analysis and subsequent maintenance recommendations depend on the selected KPIs and the agency's policy. Although the performance evaluation is an important part of PMS, they must be translated precisely into KPIs that align with the agency's overall goals and objectives (TAC 2013). Therefore, the research framework is to be developed with a KPI model that incorporates improvements in assessing the pavement performance and precisely defines the actual pavement condition.

Recently, the Mechanistic-Empirical (M-E) approach introduced the Mechanistic-Empirical Pavement Design Guide (MEPDG), which includes several improvements to traditional empirical pavement design. It also improves the accuracy of the existing design guide of the American Association of State Highway and Transportation Officials (AASHTO). The MEPDG was developed in the USA under the National Cooperative Highway Research Program (NCHRP) in 2004 to address the shortcomings of empirical pavement design methods (NCHRP 2004, Hall 2010). This MEPDG approach is being adapted by majority of highway agencies in North America, including many in Canada, to precisely predict distresses by incorporating the effect of all possible local factors, such as traffic, pavement materials and environmental conditions.

Although the pavement design and analysis are based on the M-E approach, which is now considered as the state-of-the-art pavement design practice, empirical KPIs are still used in PMS decision trees. Moreover, the incorporation of the M-E approach in assessing the overall pavement condition, rather than only applying engineering judgement, will result in precise prediction of pavement conditions and associated pavement service life. If the prediction of distresses and remaining service life of pavement is accurate and precise, a cost-effective and efficient M&R schedule can be identified for the PMS.

1.4 Research Objectives

The objective of this research is to develop cost-effective pavement M&R schedules by incorporating:

- an M-E approach into the overall condition index and
- estimates of performance indices by considering the factors affecting pavement performance.

To accomplish this, the following objectives will involve:

a. Incorporating variability analysis of existing performance evaluation practices and pavement maintenance decisions

b. Investigating estimates of existing performance indices

c. Incorporating the M-E approach: sensitivity analysis, distress prediction, comparison and verification

d. Estimating overall performance index based on MEPDG distresses and estimating the deterioration model based on traffic characteristics and material types

e. Identifying cost-effective M&R treatment options through an LCCA.

f. Developing a framework for using the M-E approach with PMS data to improve the decision-making process for pavement engineers

1.5 Thesis Organisation

The contents of the thesis are organized into ten chapters. Chapter 1 introduces the study, identifies problem areas and outlines the research hypothesis, objectives and scope. Chapter 2 reviews the literature related to current practices of pavement maintenance decisions, performance prediction methods by performance indices and application of the M-E approach. Chapter 3 discusses the proposed research methodology and the steps including data collection and analysis outlined for this study. Chapter 4 investigates variability of existing performance evaluation practices and associated maintenance decisions in PMS. Chapter 5 investigates the estimates of existing performance indices. Chapter 6 includes sensitivity evaluation of MEPDG distresses. Chapter 7 includes prediction methods of distresses based on the M-E approach and a comparison of predicted distresses to field-observed distresses. Chapter 8 includes estimation of KPI models based on the M-E approach and estimation of deterioration of overall conditions, which consider traffic characteristics and material types by both deterministic and probabilistic approaches. Chapter 9 focuses on LCCA to identify cost-effective M&R activity. Finally, Chapter 10 summarizes significant contributions, and recommendations.

CHAPTER 2
LITERATURE REVIEW

2.1 Pavement M&R Strategy

Various treatment options and methods are employed by highway agencies to restore pavement conditions and delay future deterioration. For specific climate conditions and traffic levels, the performance of the restored pavement will depend on the type of treatment and the existing pavement condition when treatments are applied. However, these relationships are not well-documented and a rational methodology for determining the optimal timing to apply specific preventive maintenance treatments are not readily available (NCHRP 2004). In Canada, there is no common convention to classify pavement routine maintenance, preservation and rehabilitation activities. Agencies across Canada describe these activities as emergency, routine, reactive, minor and major maintenance, preventive maintenance, corrective maintenance, preservation, restoration and rehabilitation. The specific activities within these categories also vary from agency-to-agency (TAC 2013).

In Ontario, a PMS analysis tool is used to facilitate the implementation of annual pavement M&R programming and investment planning at the network level. For Ontario highways, the Highway Pavement Management Application (HPMA) software package is used to select effective treatments. The HPMA M&R optimization analysis is based on the use of "cost-effectiveness". A set of decision trees are developed for each pavement section to ensure the most cost-effective pavement treatments are selected. The decision tree simulates the decision process to determine the most efficient type of M&R. A number of factors and engineering standards are considered in selecting individual treatment strategies, including road functional class, traffic volume, pavement type, age, road condition and constructability. This program is developed through a budget optimization process that determines the most cost-effective strategy for each pavement section (Ningyuan 2010).

2.1.1 Maintenance, Preservation and Rehabilitation Treatments

As per the definition of TAC Pavement Asset Design and Management Guide (PAMDG) (TAC 2013), "routine maintenance treatments are reactive and will often comprise relatively inexpensive, corrective types of strategies to immediately address specific problems such as localized potholes that may compromise the safety of road users".

"Pavement preservation normally occurs earlier in the service life of the pavement before it has reached a limit of serviceability". As per the definition of the Federal Highway Administration (FHWA) in the U.S., pavement preservation is considered as "a program employing a network level, long-term strategy that enhances pavement performance by using an integrated, cost-effective set of practices that extend pavement life, improve safety and meet motorist expectations" (TAC 2013).

Table 2.1: Commonly Used Routine Maintenance, Preservation and Rehabilitation Treatments for Flexible Pavements (TAC 2013)

Action Type	**Treatments for Flexible Pavement**
Routine maintenance	Pothole Repair Shallow Patching Drainage Improvement
Preservation	Crack Sealing Spray Patching Full Depth Patching Hot-in Place Recycling Thin Asphalt Overlay Resurfacing Functional Milling and Resurfacing-Functional Bonded Concrete Overlay Slurry Sealing Seal Coat Micro-surfacing
Rehabilitation	Resurfacing–Structural Milling and Resurfacing-Structural Cold In-Place Recycling Bonded Concrete Overlay Un-Bonded Concrete Overlay Full Depth Reclamation

"Rehabilitation consists of structural enhancements that renew the service life of an existing pavement and improve its load-carrying capacity. Rehabilitation techniques include structural restoration treatments and structural overlays. Rehabilitation may also be used to strengthen pavement that will be subjected to higher than originally estimated traffic loads" (TAC 2013).

The life cycle of typical pavement starts with initial construction and is followed by various forms of maintenance, including preventive, routine and corrective maintenance as needed. Routine maintenance treatments are generally reactive and relatively inexpensive. Corrective maintenance treatments are applied immediately to address specific problems. Pavement preservation treatments are normally applied early in the pavement's service life before reaching its limit of serviceability. Pavement rehabilitation consists of structural enhancements that improve the service life of existing pavement as well as its load-carrying capacity (TAC 2013). Table 2.1 shows commonly used routine maintenance, preservation and rehabilitation treatments in Canada.

However, selecting the appropriate M&R strategy is a key step to achieve a sustainable pavement management process. It requires detailed analysis for priority selection among road sections and consideration of the cost-benefit analysis within the available budget. It is observed from recent studies that LCCAs mainly focus on cost-effectiveness.

2.1.2 Cost – Effective M&R Schedule

Cost and effectiveness are often demarcated for each alternative treatment before selection. Cost components generally include construction or various M&R costs and user costs, such as traffic diversion and operation costs caused by roughness. Effectiveness is measured in different ways by different agencies. Effectiveness is defined in terms of the overall index performance improvement. It is estimated based on the life extension resulting from the treatment or the area between the treated and non-treated pavement. Generally, agencies consider improved remaining service life, increased PCI or increased area under the performance curve. This effectiveness is divided by cost (similar to a benefit/cost ratio). Generally, the effectiveness of a strategy is measured in terms of the area between the treated and non-treated overall index performance curves. This area is calculated as the area between the curves, as illustrated in Figure 2.1. When a treatment is delayed beyond the overall index-need year, a dis-effectiveness amount is subtracted from the effectiveness area as illustrated in Figure 2.2.

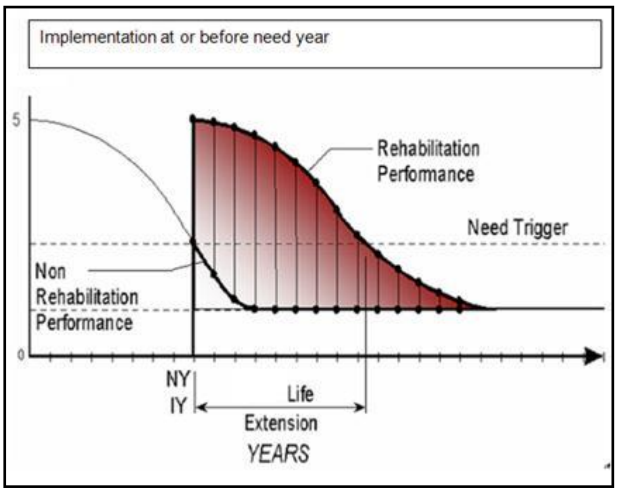


Figure 2.1: Area under Predicted Pavement Performance Curve (HPMA 2012)

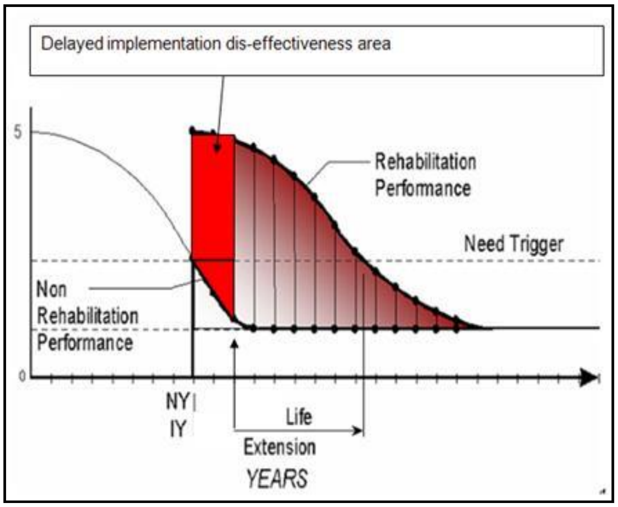


Figure 2.2: Area under Predicted Pavement Performance Curve for Delayed M&R Treatment (HPMA 2012)

In HPMA, the M&R strategy analysis process is based on the decision trees that were developed based on experts' experience and historical pavement performance records. Trees are defined by functional class and pavement type. Decision trees define the feasible strategies under various conditions. Each treatment alternative selected based on the decision tree is analyzed in terms of life cycle costs and performance (index or individual distresses predicted). The optimization analysis also includes a user-defined budget and performance constraints for a programming period of up to 30 years. The optimization uses either a marginal cost-effectiveness approach or linear programming. This analysis involves performing M&R analysis for the entire period, followed by running optimization analyses incorporating various optimization scenarios using M&R analysis results (HPMA 2012). Figure 2.3 shows the framework of HPMA M&R analysis.

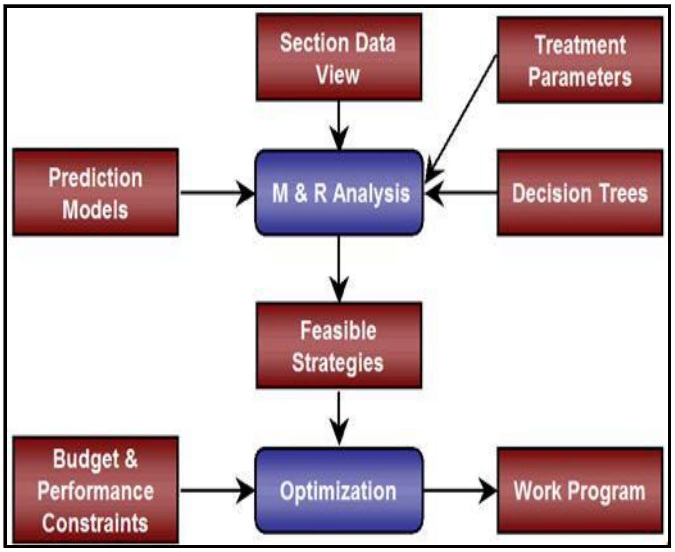


Figure 2.3: Framework of HPMA M&R Analysis (HPMA 2012)

To improve the cost-effectiveness method for pavement M&R schedules, a number of research alternatives are carried out.

Environmental damage cost (EDC) is also considered as an indicator of cost-effectiveness. Yu (2013) integrated EDC with LCCA to improve the pavement maintenance optimization methodology. This study used a combined Life Cycle Cost Assessment (LCCA)—LCCA model to optimize the pavement maintenance plans by incorporating EDC.

Mandapaka (2012) evaluated and selected an optimal M&R strategy for a flexible pavement road section by integrating LCCA and California Mechanistic-Empirical (CalM-E) design procedures. LCCA was carried out by using the M-E approach predicted distresses in an integrated way. However, this study investigated only one road section for selected distresses of MEPDG. The overall performance of KPIs are not considered for LCCA, which is generally used for M&R schedules. Therefore, this method for PMS may not be helpful if the M&R strategy is based on overall performance of road sections and setting a priority at the network level.

De la Graza (2010) developed a decision-making tool for network-level optimization for pavement maintenance programming issues through linear programming. This decision-making tool presents alternative highway maintenance strategies through an automated process in Microsoft Excel. A total of nine treatment types with unit prices are analyzed over a 15-year period. However, this study only focused on budget allocation processes dependent on lane-mile conditions.

Ningyuan (2001) presented an integrated dynamic performance prediction for pavement M&R optimization methodology. This optimization model considered cost-effectiveness based on multi-year priority programming. This study selected an M&R strategy based on predicted improved PCI value. Improvement of PCI value is predicted based on the historical record of that treatment type. However, the traffic, materials, weather and other local factors may have significant influence on predicted pavement serviceability. The M-E analysis improves this prediction of pavement conditions.

Labi (2005) investigated the cost-effectiveness of various levels of life cycle preventive maintenance for three asphaltic concrete pavement functional class families. This study estimated cost-effectiveness using existing performance models, performance jump models and cost models for each treatment type. However, performance jump models were not based on the M-E analysis.

Whiteley (2005) considered the variability associated with the discount rate and incorporated all associated variability into the LCCA of the asphalt overlay sections taken from the Canadian Long Term Pavement Performance (C-LTPP) project. With the LCCA values for typical design life, a sensitivity analysis was performed to evaluate the impact of 10%, 20%, and 30% differences in the in-service performance compared to the design life. These LCCA differences were then used as a basis for establishing pay factors. However, variability factors such as overlay thickness variation, total prior cracking variation and accumulated Equivalent Single Axle Loads (ESALs) after an eight-year variation are considered in the LCCA of this study.

From the studies outlined above, it is observed that each mainly focused on the comparison of treatment options. The overall condition of pavement is neither investigated nor estimated in the LCCAs. Some studies (Mandapaka 2012) did compare single-cracking predicted by the M-E approach. However, road condition assessments using a failure trigger value of single-cracking might not capture the actual overall conditions of the road.

This study will compare the overall condition and deterioration of pavement with consideration of predicted distresses from the M-E approach.

2.2 Key Performance Index, and Method of Estimates used for Assessing Overall Condition of Pavement

Ontario highway systems use evaluation indices, such as PCI, the Distress Manifestation Index (DMI), IRI and the Riding Comfort Index (RCI) to evaluate pavement conditions. The KPIs used in the MTO PMS 2 are shown in Table 2.2 (Ningyuan 2004).

Table 2.2: Performance Indices Used in Ontario Highways

Key Performance Index	Performance Measure	Use Level
Technical Measures		
PCI	Assessment of overall pavement conditions, structural strength and functional serviceability of both network and individual pavement sections	PCI is currently used by regions to generate an annual pavement maintenance program and investment planning strategies
DMI	Overall pavement surface conditions for individual pavement sections and network	DMI is used to support PCI and is favored by regions that have lower-class roads
IRI	Evaluation of pavement riding quality in terms of roughness or smoothness	Pavement roughness data is collected by use of high-speed inertial profilers
Riding Comfort Rating (RCR)	Evaluation of pavement riding quality in terms of user comfortableness	RCR was collected prior to IRI data
Skid Number	Pavement surface skid resistance	Measured at project level on a request basis
Rut depth in mm measured in both left and right wheel paths	Transverse profiles and rutting measurement	Rutting is measured at network level using high-speed equipment
Structural Adequacy Index (SAI) or deflection value measured by FWD equipment	Assessment of pavement structural strength or service life	Currently used at project level
Economic Measures		
Highway Agency cost, social and economic impacts and road user costs	Maintenance, service life, traffic accidents and travel costs, travel time and travel time reliability	To be included in the PMS-2 analysis function

The PCI is an index that incorporates the type of distress, density of distress, severity of distress and roughness. It is a subjective method that shows a numerical rating of the pavement surface condition and varies from 0 (failure) to 100 (excellent) (AASHTO 1993). PCI is measured for pavement distresses and severity and the smoothness and ride comfort of the road. PCI records all distresses and each distress has its own weighting based on its overall impact on pavement performance (TAC 2013). Most studies on pavement performance indices available are mainly based on the existing practice of performance indices used in PMS by different agencies.

In the USA and Europe, different performance indices are used. A recent study presented a comparison of performance management practices in the USA and Europe (Van Der Lei 2014). KPIs were developed and chosen once the goals of the corresponding agency were determined. In a similar study, Lea (2014) studied the initial configuration of California's PMS, focusing on the aggregation of pavement data from their automated surveys. For small communities, PMS are different than highways, which consider different modules (Avakoli 1992).

In PMS, the estimation method for performance index models are found in different ways in alternate research studies. These are discussed below:

A probabilistic approach is used to assess the reliability of pavement sections. The analysis is based on the use of probabilistic duration modeling techniques by hazard function (Prozzi 2000). Application of joint estimates were observed in developing the performance index model. Pavement performance index models were developed from a combination of experimental and field data. A riding quality model based on serviceability consideration was also developed. The original model parameters were re-estimated by applying joint estimation to the field data set. It is observed that duration models investigated the stochastic nature of pavement failure time (Prozzi 2004). The 'linear mixed effects model' was developed to predict future pavement conditions. This model was developed by a weighted combination of the average deterioration trend and past conditions of the pavement (Yu 2003). Non-linear models were also developed for KPIs for realistic prediction of pavement conditions (Prozzi 2003). In this study, the KPI model is developed by considering traffic characteristics, pavement structural properties and environmental conditions. Moreover, the effect of KPI model accuracy is also investigated on optimal design and life cycle costs by using regression and probabilistic models (Madanat 2002). In a similar study, the effectiveness of the estimation of rutting models is also investigated (Archilla 2001). In this study, estimation to identify parameters is found by integrating information from two data sources, the AASHO and the WesTrack road tests. Furthermore, the effect of different statistical assumptions and estimation techniques of KPI models on predictive capabilities are also explored by using AASHO road test data (Chu 2008). An approach of applying mathematical techniques to fuzzy sets are found to categorize the subjective ratings of the severity and extent of pavement distress (Bandara 2011).

For evaluating the pavement performance of the roads, different sectioning methods are found. Although different KPIs and methods are used to evaluate pavement, accurate location referencing is often overlooked. However, this is a very important aspect for pavement evaluation and management. Accurate location referencing enables division of the network into homogeneous pavement sections. The procedure of forming homogenous sections is known as sectioning or segmentation (TAC, 2013). Different agencies use different road sectioning methods. Generally, three sectioning methods are used commonly in PMS: fixed length sectioning method, dynamic sectioning method and static sectioning method (Bennett 2007).

Generally, fixed length sectioning methods divide each road into fixed lengths, typically between 100m to 500m. Although, this method is considered suitable because it overcomes most of the statistical limitations compared to other methods, it continues to be complex in determining the appropriate lengths of treatments. Also it becomes problematic over time when future development render portions of the section 'non-typical'.

The dynamic sectioning method uses road condition data stored at relatively short intervals, amalgamating sections into variable lengths and ensuring that the conditions and inventory data fall within certain homogeneity rules. In this method, sections are analysed in the homogeneous lengths and it can result in many, very short sections. This method has limitations in that sectioning changes every year pending the outcomes of condition surveys.

The static sectioning method uses a level of dynamic sections and is popular among road agencies. This method is different because once homogenous sections are amalgamated, they remain constant for a while. Its limitation is that the sectioning is only valid for a short period of time and if agencies do not review the sections regularly, it may result in uninformed maintenance decisions and outcomes.

In Ontario, KPI models are developed from road condition surveys for selected distresses. These models are developed based on the weightage of such distresses that are evaluated or rated in a subjective manner. These weights are assigned by the MTO to 15 distress categories, which are dependent on the highway type (MTO, 2007).

A number of researchers investigated the evaluation of pavement performance models or performance management practices. The DMI model was evaluated by using automated distress evaluation data in Southern Ontario (Tighe 2008). The randomized block design (RBD) approach was used for the hypothesis test in this study. A hypothesis test was performed to determine the differences in the DMI model on the basis of automated evaluation data.

The joint estimation approach for the development of pavement performance models was found in the Minnesota Road Research Project (MnRoad) (Prozzi 2004). In this study, the riding quality model was developed by joint estimation in terms of IRI from MnRoad data. A nonlinear serviceability model was developed by using the same data set and variables as the equivalent existing linear model. The error of the new model was found to be half of the existing model. Investigations on the effectiveness of practicing performance indicators were done by the New Zealand Transport Agency (NZTA) (Henning 2013). In this study, a new measure 'rutting index (RI)' was developed with the goal that RI could effectively quantify the structural performance and behaviour of the pavement. This RI was calculated for both network data and long-term pavement performance (LTPP) data. However, such RI was developed based on the OLS approach. Probabilistic duration modeling techniques were also used in the investigation of performance measures during road design and construction (Molenaar 2011). Weibull regression was also used in a study on California Pavement Management Systems (Lea 2014).

As opposed to the OLS approach, Zellner formulated the SUR estimator that accounts for contemporaneous correlations among multiple dependent variables in a suit of regression models (Zellner 2006, and Cadavez 2012). This method uses a set of equations that are contemporaneously correlated and share a common random error structure with non-zero covariance. The SUR method estimates the parameters of all equations simultaneously. In this process, the parameters of each equation take the information provided by the other equations into account. On the other hand, calculating separate OLS-based solutions ignores any correlation among the random errors across equations. Since the dependent variables are correlated, design matrices may contain some of the same variables. Consequently, there may be contemporaneous correlation among the errors across the equations. For this reason, SUR models are often applied when there may be several equations, which appear to be apparently unrelated to the naked eye. In SUR models, the results contribute in better estimates of the parameters compared to those in OLS (Prozzi 2004 and Zellner 1962). The efficiency of estimation increases with higher correlation among the random error terms of the different equations. It also considers the effects of larger sample sizes and multi-collinearity between the regressors (Cadavez 2012, Moon 2006, Kubáček 2013, Takada 1995 and Powell 2000).

Recently, the SUR approach was applied to capture the deterioration process of pavement performance (Prozzi 2008). This study applied the SUR approach to the simultaneous estimation of pavement performance deterioration models. The deterioration of two major indicators, IRI, and rut depth were investigated in this model system. The results showed improved performance characterization and more accurate forecasting for IRI and rut depth.

The SUR approach is also used to predict the pavement performance over time for Indiana roads (Anastasopoulos 2014). In this study, the service life of the pavement was determined using forecasts and historical thresholds, and random parameters of duration models were estimated to identify influential factors affecting pavement service life.

Most of the agencies estimated KPI models separately. In developing KPI models for PMS, empirical regression is proven to be an effective way to characterize the relationship between the independent variables and the dependent variable. However, if the unobserved factors affecting pavement performance are correlated, joint estimation of KPI models will be a more accurate methodology than estimation by OLS.

Although recent research has contributed significantly to developing the KPI models based on the factors affecting the performance, these are not estimated jointly. Recently, the application of SUR show accurate estimates when unobserved factors are correlated in joint estimation (Prozzi 2008, and Anastasopoulos 2014). This study focuses on the joint estimation of the major KPI models, considering all available performance variables as independent variables for Ontario highways.

2.3 Adapting Mechanistic-Empirical Approach in Pavement Design

The first empirical methods for flexible pavement design were developed during the mid-1920s when the first soil classifications were developed. In 1992, the Public Roads (PR) soil classification system was published and the California Highway Department developed a method using the California Bearing Ratio (CBR) strength test. In 1945, the Highway Research Board (HRB) modified the PR classification and soils were grouped into seven categories (A-1 to A-7) with indices to differentiate soils within each group. This classification was applied to estimate the sub-base quality and total pavement thicknesses (Schwartz 2007). In the 1950s, pavement design methods were revised based on a limited amount of performance data acquired through road tests sponsored by the AASHO. The empirical design equations were developed based on the road test results and the AASHTO Interim Guide for the Design of Pavement Structures was later published in 1972 (Dzotepe 2011). This Interim Guide was developed mainly based on the AASHO road tests with limited range of design parameters. It includes only one climate, one sub-grade, two years duration, limited cross sections, 1950s materials, traffic volumes, specifications and construction methods. Covering some improvements with regard to material input parameters and design reliability, this guide was updated in 1986 and 1993 (AASHTO 2008).

However, the previous pavement design guide did not consider the variation of the materials, climate and traffic of highways for different locations. For this reason, the empirical design method result is considered to be less accurate and precise. To address this limitation and utilize mechanistic-based models, AASHTO initiated further investigation and research in the mid-1990s, aiming to develop a new pavement design guide. Finally, AASHTO and the NCHRP developed the MEPDG under NCHRP Project 1-37A in 2004 (Timm 2010, and Hall 2010). In the M-E approach, a mathematical model is used to define the relationship between different physical and structural responses (stresses and strains). According to Flintsch and McGhee, M-E procedures use pavement models based on the mechanics of materials to predict pavement responses (deflections, strains and stresses) and empirically-based transfer functions to estimate distress initiation and development based on these responses" (Flintsch 2009). Figure 2.4 presents the basis of the M-E design process. The flow chart of design procedures of the MEPDG is shown in Figure 2.5.

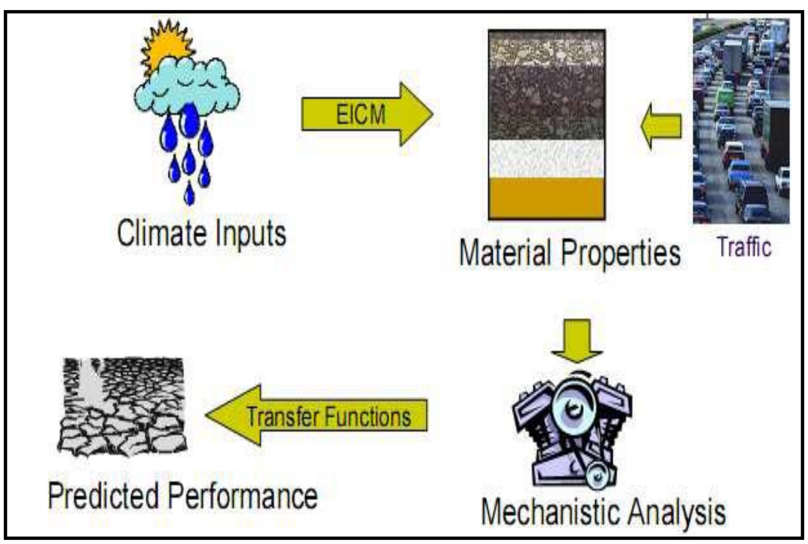


Figure 2.4: Basis of M-E Design Process (Yu 2013)

The recent MEPDG software, AASHTOWare Pavement M-E Design (version 2.0) is the next generation of pavement design software, building upon the NCHRP MEPDG.

2.3.1 MEPDG Distresses for Flexible Pavements

The MEPDG performance predictions consist of pavement distresses and ride quality. For flexible pavement, the following distresses are predicted in the MEPDG:

- AC Bottom-Up Fatigue Cracking (%),
- Top-Down Fatigue Cracking (m/km),
- Total Cracking including Reflective and Alligator (%),
- AC Thermal Fracture (m/km),
- Permanent Deformation Total for AC only (mm)
- Terminal IRI (m/km)

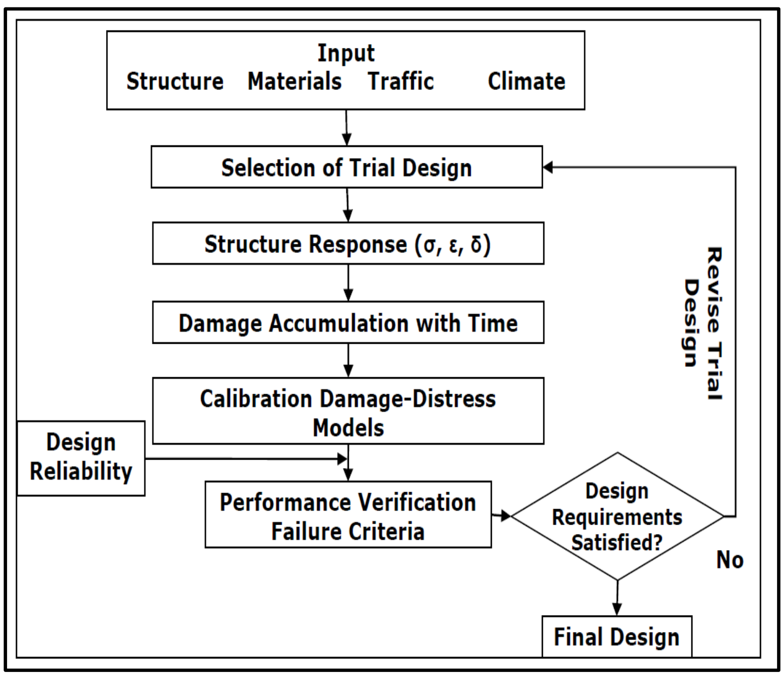


Figure 2.5: Flow chart of MEPDG Procedure (NCHRP 2004)

AC Bottom-Up/Alligator Fatigue Cracking

This cracking is a form of fatigue or wheel load-related cracking and is defined as a series of interconnected cracks initiated at the bottom of the AC layers.

Tensile and shear stresses developed at the bottom of the AC layer due to repeated traffic loads is critical for structural stability of the pavement layer. The horizontal tensile strain is developed at the bottom of the asphalt bound layer and due to excessive repetitive loads on the pavement surface, cracking of the layer will result. After the damage is initiated at the critical location, these cracks propagate along with accumulative traffic loading. Figure 2.6 shows the formation pattern of bottom-up cracking in the AC layer. Alligator cracking is calculated as a percentage of the total lane area in the MEPDG (AASHTO 2008).

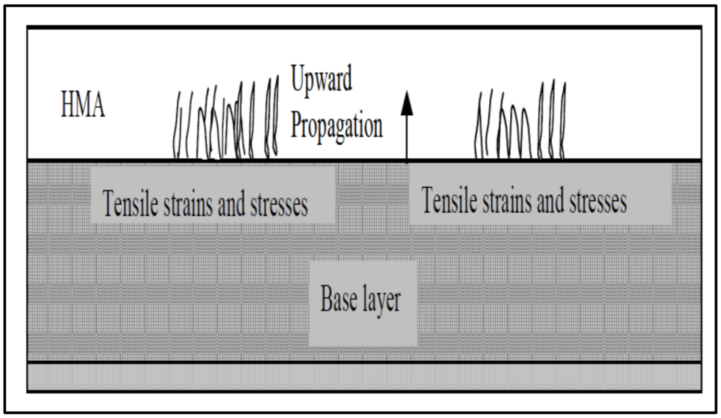


Figure 2.6: Formation of AC Bottom-UP Fatigue Cracks in Pavement (NCHRP 2004)

AC Top-Down / Longitudinal Fatigue Cracking
This cracking occurs within the wheel path and are defined as cracks predominately parallel to the pavement centerline. Longitudinal cracks at the surface of the pavement initially show up as short longitudinal cracks that become connected with continued truck loadings. Raveling or crack deterioration may occur along the edges of these cracks, but they do not form an alligator cracking pattern. Figure 2.7 shows the formation pattern of top-down cracking in AC layer.

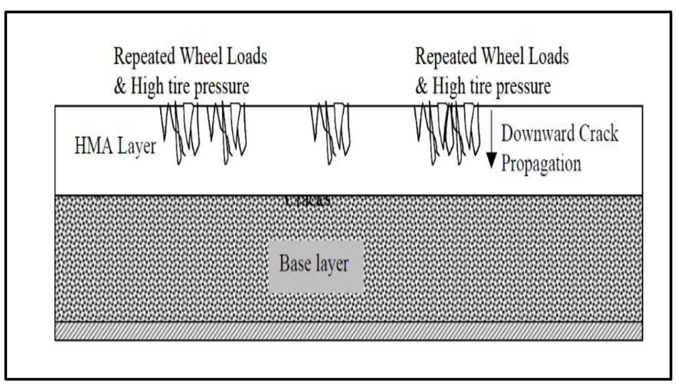


Figure 2.7: Formation of AC Top-Down Fatigue Cracks in Pavement (NCHRP 2004)

The unit of longitudinal cracking calculated by the MEPDG is total meters per kilometer (m/km), including both wheel paths (AASHTO 2008). In thick pavements, cracks are more likely to initiate from the top in localized areas of high tensile stresses due to tire-pavement interaction and asphalt binder aging (Myers 2001).

Thermal Fracture or Thermal Cracking

Transverse cracking or non-wheel load-related cracking is predominately perpendicular to the pavement centerline and caused by low temperatures or thermal cycling. They tend to appear on the surface. The shrinkage of the AC surface due to low temperatures or daily and seasonal temperature differences and asphalt binder hardening are considered to be major reasons for this type of cracking. The unit of transverse cracking is calculated by the MEPDG in meters per kilometer (feet per mile) (AASHTO 2008).

Permanent Deformation or Rutting

Permanent deformation is a longitudinal surface depression in the wheel path, resulting from plastic or permanent deformation in each pavement layer. This depression may form in any of a pavement's layers or subgrade due to consolidation or lateral movement of materials under traffic and environmental loadings. Rutting damage due to different axle configurations is approximately proportionate to the number of axles within an axle group (Chatti 2009). This depression could be the result of traffic loading, poor compaction of layers during the construction stage or the shearing of the pavement caused by traffic-wheel loading (AASHTO 2008). The unit of rutting calculated by the MEPDG is in millimeters and represents the maximum mean rut depth between both wheel paths. The MEPDG also computes the rut depths within the AC and the total pavement structure.

International Roughness Index (IRI)

Pavement roughness is generally defined as an expression of irregularities in the pavement surface that adversely affect the ride quality of a vehicle. IRI is used to determine the functional serviceability or adequacy of the pavement. IRI was developed by the World Bank in the 1980s (WSDOT 2005) to define a characteristic of the longitudinal profile of a traveled wheel-track and constitutes as a standardized roughness measurement. The commonly recommended units are meters per kilometer (m/km) or millimeters per meter (mm/m). In MEPDG, IRI is predicted empirically as a function of pavement distresses and site factors that represent a foundation's swell or shrink and frost-heave capabilities (ASSHTO 2008).

2.3.2 MEPDG Prediction Models for Flexible Pavements

MEPDG predicts the critical responses following the M-E analyses and using equations known as prediction models. These models are used for different distress types and are discussed below:

Bottom-Up and Top-Down Fatigue Cracking

The MEPDG assumes that alligator or area cracks initiate at the bottom of the AC layers and propagate to the surface due to continued truck traffic, while longitudinal cracks are assumed to initiate at the surface. The most commonly used model to predict the number of load repetitions to fatigue cracking is a function of the tensile strain and mix stiffness (modulus). Generally, the allowable number of axle-load applications required for the incremental damage index approach to predict both types of load-related cracks (alligator and longitudinal) is shown by the general equation below with different transfer functions based on different research (Yang 1993, NCHRP 2004, Walid 2001, Salem 2008 and Hsiang et al. 2007).

$$N_f = f_1(\varepsilon_t)^{-f_2}(E_1)^{-f_3} \tag{2.1}$$

Where,
N_f = Number of repetitions to fatigue cracking
E_1 = Modulus of HMA (MPa or psi)
ε_t = tensile strain at critical locations (mm/mm or in/in)
$f_1, f_2, f_3 =$ Laboratory regression coefficient

The critical locations of the tensile strains may either be at the surface (result in top-down cracking) or at the bottom of the asphaltic layer (result in bottom-up cracking). AC fatigue equations used in AASHTOWare Pavement M-E are:

$$N_f = C\ Bf_1\ k_1(1/\varepsilon_t)^{k_2 Bf_2}(E_1)^{k_3 Bf_3} \tag{2.2}$$

Where,
N_f = Number of load repetitions to failure
ε_t = Tensile strain at the critical position (mm/mm)
C= Transfer function regression constants
E = Material stiffness (Mpa or psi)
k_1, k_2, k_3 = Global field calibration parameters
Bf_1, Bf_2, Bf_3, = Local or mixture specific field calibration constants

The area of bottom-up fatigue or alligator cracking and length of longitudinal cracking are calculated from the total damage over time using different transfer functions. The relationship used to predict the amount of bottom-up fatigue cracking on an area basis is as follows:

$$FC_{\ bottom} = \left(\frac{C_3}{1+e\ \hat{}\ \left(C_{1*} C'_1 - C_2 * C'_2 * log10\,(D*100\,)\right)}\right) * \left(\frac{1}{60}\right) \tag{2.3}$$

Where,
$C_{1,2,4}$ = Transfer function regression constants
FC_{bottom} = Area of alligator cracking that initiates at the bottom of the HMA layers (% of total lane area)
D = Cumulative damage index at the bottom of the HMA layers

$$FC_{top} = \left(\frac{C_4}{1+\ e^{(\,C_1 - C_2 * log10\,(Damage))}}\right) * 10.56 \tag{2.4}$$

Where,
FC_{top}= Length of Longitudinal Cracks at the Top of the HMA Layer (m/km)
$C_{1,2,4}$ = Transfer Function Regression Constants
D = Cumulative Damage Index at the Top of the HMA Surface

Cumulative Damage Index is expressed as:

$$D = \sum(\Delta D)_{j,m,i,p,T} = \sum\left(\frac{n}{N}\right)_{j,m,i,p,T} \tag{2.5}$$

Where,
n = Actual number of axle-load applications within a specific time period,
j = Axle-load interval,
m = Axle-load type (single, tandem, tridem, quad, or special axle configuration,
I = Truck type using the truck classification groups included in the MEPDG,
p = Month, and
T = Median temperature for the five temperature intervals or quintiles used to subdivide each month

Thermal Fracture or Thermal Cracking

The amount of crack propagation induced by a given thermal cooling cycle is predicted using the Paris law of crack (AASHTO 2008):

$$\Delta C = A\,(\Delta K)^n \tag{2.6}$$

Where,
ΔC = Change in the Crack Depth due to a Cooling Cycle
ΔK = Change in the Stress Intensity Factor due to a Cooling Cycle
A, n = Fracture Parameters for the HMA Mixture

'A' and '*n'* can be obtained from the indirect tensile creep-compliance and strength of the HMA:

$$A = 10^{k,\,\beta,\,(4.389-2.52Log(E\ \sigma_m n))} \tag{2.7}$$

$$n = 0.8[1 + \frac{1}{m}] \tag{2.8}$$

Where,
k = Coefficient determined through global calibration for each input level (Level 1 = 5.0; Level 2 = 1.5; and Level 3 = 3.0)
E = HMA indirect tensile modulus
σ_m = Mixture tensile strength

m = The m-value derived from the indirect tensile creep compliance curve measured in the laboratory and

β = Local or mixture calibration factor

The degree of cracking is predicted by the MEPDG using an assumed relationship between the probability distribution of the log of crack depth to AC layer thickness ratio and the percentage of cracking. The thermal cracking model used in the AASHTOWare Pavement M-E is expressed as (AASHTO 2008) is:

$$TC = \beta_{t1}\; N\,[\frac{1}{\sigma_d}\; Log\left(\frac{C_d}{H_{ac}}\right)] \tag{2.9}$$

TC = Observed amount of thermal cracking (m/km)
β_{t1} = Calibration Parameter

$N_{[z]}$ = Standard normal distribution evaluated at [z]

σ_d= Standard deviation of the log of the depth of cracks in the pavement (mm)
Cd = Crack depth (mm)
H_{ac} = Thickness of AC layers (mm)

Permanent Deformation or Rutting Models
Several rutting models are developed to relate the asphalt modulus and/or the measured strains to the number of load repetitions to pavement failure in different researches. Most of the number of load repetitions to pavement failure take the following form (Yang 1993, Salem 2008, Wardle 1998, Jackson 2007 and Mathew 2007):

$$N_d == f_4\,(\varepsilon_c)^{-f_5} \tag{2.10}$$

Where,
N_d = number of load repetitions;
ε_c = Vertical compressive strains on the top of subgrade

The rate or accumulation of plastic deformation is measured in the laboratory using repeated load permanent deformation triaxial tests for both HMA mixtures and unbound materials. The laboratory derived relationship is then adjusted to match the rut depth measured on the roadway. For all HMA mixtures, the MEPDG field calibrated form of the laboratory derived relationship from repeated load permanent deformation tests is as follows:

$$\Delta_{p\,(HMA)} = \varepsilon_{p\,(HMA)}\, h_{\,HMA} = \beta_1\, k_z\, \varepsilon_{r\;(HMA)}\,(10)^{k_{1r}}\;(n)^{k_{2r}\,\beta_{2r}}\,(T)^{k_{3r}\beta_{3r}} \tag{2.11}$$

Where,
$\Delta_{p\,(HMA)}$=Accumulated permanent or plastic vertical deformation in the

HMA layer/sublayer (mm)

$\varepsilon_{p\ (HMA)}$ =Accumulated permanent or plastic axial strain in the HMA layer/sublayer (mm/mm)

$\varepsilon_{r\ (HMA)}$ =Resilient or elastic strain calculated by the structural response model at the mid-depth of each HMA sublayer (mm/mm)

h_{HMA} =Thickness of the HMA layer/sublayer (mm)

n= Number of axle-load repetitions

T= Mix or pavement temperature (0C)

k_z =Depth confinement factor

k_{1r}, k_{2r}, k_{3r} = Global field calibration parameters

$\beta_{1r}, \beta_{2r}, \beta_{3r}$ = Local or mixture field calibration constants

To calculate plastic vertical deformation within all unbound pavement sublayers and the foundation or embankment soil, the following mathematical equation is used.

$$\Delta_{p\ (soil)} = B_{s1}\ k_{s1}\ \varepsilon_v\ h_{soil}\ \ (\varepsilon_{o/}\varepsilon_r)\ e^{-(\frac{p}{n})^{\beta}} \tag{2.12}$$

Where,

$\Delta_{p\ (soil)}$=Permanent or plastic deformation for the layer/sublayer (mm)

n= Number of axle-load applications

ε_o = Intercept determined from laboratory repeated load permanent deformation

ε_v= Average vertical resilient or elastic strain in the layer/sublayer and calculated by the structural response model sublayer (mm/mm)

ε_r= Resilient strain imposed in laboratory test to obtain material properties ε_o , β and p, (mm/mm)

h_{soil}= Thickness of the unbound layer/sublayer (mm)

ks_1 = Global calibration coefficients (for fine and granular)

β_{s1} = Local calibration constant for the rutting in the unbound layer

Total rut depth is calculated as sum of layers and the relationship is as follows:

$$RD = \sum_{i=1}^{n} \varepsilon_{pi}\ \ h_i \tag{2.13}$$

Where,

RD = pavement permanent deformation (mm)

n = number of sublayers

εp_i = total plastic strain in sublayer i (mm/mm)

h_i = thickness of sublayer i (mm)

IRI Models

All the aforementioned distresses predicted by the M-E models are correlated to roughness. In addition, the smoothness model alternatively considers other distresses, such as potholes, longitudinal cracking outside wheel paths and block cracking if there is a potential of occurrence. The design premise included in the MEPDG for predicting smoothness degradation is that the occurrence of surface distress will result in increased roughness (increasing IRI value) or in other words, a reduction in smoothness. (AASHTO 2008) and shown in the equation below:

$$IRI = IRI_0 + f_1\,(SF) + f_2\,(FC\ Total) + f_3\,(TC) + f_4(RD) \qquad (2.14)$$

Where,
IRIo = Initial IRI after construction (mm/km)
SF = Site factor
FC Total = Area of fatigue cracking (combined alligator, longitudinal, and reflection cracking in the wheel path) (percent of total lane area)
TC = Length of transverse cracking (including the reflection of transverse cracks in existing HMA pavements) (mm/km)
RD = Average rut depth (mm)

The site factor (SF) is calculated in accordance with the following equation:

$$SF=Age[0.2003(PI+1)+0.007947\{Precip/25.4)+1\}+0.000636(FI+1) \qquad (2.15)$$

Where,
Age = Pavement age (year)
PI = Percent plasticity index of the soil,
FI = Average annual freezing index, of days, and
Precip = Average annual precipitation or rainfall (mm)

2.3.3 MEPDG Distress Models: Application into PMS

The performance prediction is dependent on local factors illustrated in Figure 2.8. As a result, it is important to evaluate the performance prediction models and to re-calibrate these performance prediction models for local characteristics. To calibrate these models, a number of researchers conducted studies (Hall 2010; Hoegh 2008, Velasquez 2009, Darter 2005 and Ali 1998) for different locations and different transportation agencies.

Hoegh (2010) conducted local calibration of the rutting model using time history rutting performance data for pavement sections at the Minnesota Department of Transportation. In this study, a detailed comparison of the predicted total rutting, asphalt layer rutting and measured rutting is carried out. Predicted rutting was recalibrated by adjusting the parameters and reducing an error between predicted and measured performance. However, the results show that the local calibrated models are less biased than the predictions used by global calibrated rutting models.

Hall (2010) summarized the initial local calibration of flexible pavement models in the MEPDG for Arkansas. It is found that for the current MEPDG, predicted distresses did not accurately reflect measured distresses, particularly for longitudinal and transverse cracking. However, due to the lack of measured transverse cracking, the transverse cracking model is not calibrated. Finally, the procedure for local calibration of the MEPDG using LTPP and PMS data in Arkansas is established.

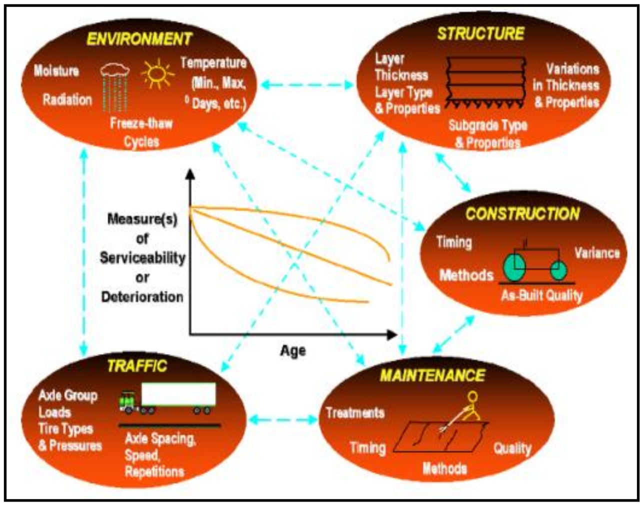


Figure 2.8: Factors affecting Pavement Performance (Tighe 2007)

Siraj (2009) verified the accuracy of the predicted performance from the MEPDG software for the state of New Jersey for Level 2 and Level 3 inputs. In this verification, nine LTPP and 16 non-LTPP sections in the state of New Jersey were evaluated. The measured longitudinal cracking, thermal cracking and roughness (IRI) are found statistically similar to the predicted values. However, the prediction of MEPDG software 1.0 was not accurate for IRI.

Velasquez (2009) analysed the performance prediction and evaluated different types of flexible and rigid pavements for local conditions. The results show that the local adaptation for Minnesota conditions require modification in both the MEPDG rutting model for base and subgrade and coefficients in the MEPDG fatigue cracking and thermal cracking models for flexible pavements. However, the use of the longitudinal cracking model is not recommended for adaptation since the IRI model could not be locally calibrated.

Kang (2007) standardized two important calibration factors, longitudinal and alligator fatigue cracking models. The calibrated models in the MEPDG validate the reliable prediction of pavement distresses. Moulthrop (2007) calibrated MEPDG distress transfer functions for flexible and semi-rigid pavements of Montana. The results show that fatigue cracking (bottom-up) model is reasonable, developing a local calibration factor for predicting thermal cracking. However, for the top-down fatigue cracking model, no consistent trend in the predictions is identified to reduce bias and standard error.

Schram (2006) analyzed PMS data of Nebraska to calibrate two smoothness models at the project level. Based on the study results, it is revealed that project-level calibrations reduced default model prediction error by nearly twice than the network-level calibration. This study offers a space into the accuracy that can be achieved with local calibrations.

Ali (1998) evaluated and calibrated MEPDG performance models using the LTPP data for specific loading and environmental conditions. The predicted performance of various sections are compared with observed in-service fatigue cracking and rutting for various pavements. However, it is evident that more data is required for a more conclusive evaluation, since rutting models showed poor agreement with the observed rutting.

Several sensitivity analyses were conducted to address and understand the influential inputs of the MEPDG process. NCHRP (NCHRP 2013) analyzed five pavement types: new Hot-Mix Asphalt (HMA), HMA over a stiff foundation, new Jointed Plain Concrete Pavement (JPCP), JPCP over a stiff foundation and new Continuously Reinforced Concrete Pavement (CRCP). In this study, a normalized sensitivity index was adopted as the quantitative metric. NCHRP (NCHRP 2011) also carried out global sensitivity analyses for five pavement types under five climate conditions and three traffic levels.

Retherford (2011) developed Gaussian Process (GP) surrogate models for each relevant distress model. The GP models were used for sensitivity analysis and design optimization.

Graves (2011) carried out a sampling-based global sensitivity analysis to identify influential variables of the parameters. Orobio (2011) conducted space-filling computer experiments with latin hypercube sampling, standardized regression coefficients and Gaussian stochastic processes to categorize the relative importance of the material inputs in MEPDG for flexible pavement. Moya (2011) conducted a case study of a pavement structure by considering several pavement design variables as random. Sensitivity of rutting and other distresses to input parameters (rutting sensitive to thin layer) are presented for different countries (TRC 2011). The impact of accurate traffic inputs in forecasting traffic loads for pavement design are also analyzed (Hajek 2011). MEPDG key inputs such as hot-mix asphalt, base nominal aggregate size, climate location, HMA thickness, AADTT, subgrade strength, truck traffic category, construction season and binder grade are analyzed and discussed using local sensitivity (Amador -Jime´nez 2011). Siraj (2009) verified the accuracy of the predicted performance from the MEPDG software for the state of New Jersey for Level 2 and Level 3 inputs. Guclu (2009) carried out sensitivity for JPCP and the design input variables were categorized as being most sensitive, moderately sensitive or least sensitive in terms of their relative effect on distresses. Hall (2005) assessed the relative sensitivity of the models used in the M-E design guide for inputs relating to Portland cement concrete materials of JPCP.

2.4 Summary of Relevant Literature Review

The recent research work related to pavement performance evaluation, MEPDG distress models, LCCA and cost-benefit analysis is summarized in Table 2.3.

Table 2.3: Summary of Recent Relevant Research Findings

Relevant Research Area	**Author/ Authors**	**Research Summary**	**Remarks**
Effectiveness of Using Various KPIs	Henning (2013)	Investigated the effectiveness of using various KPIs. Rutting Index (RI) was developed with the objective to effectively quantify the structural performance of pavement in New Zealand.	This study is useful if rut depth is used as an index for maintenance decisions.
Probabilistic Approach in Estimating Performance Index	(Prozzi 2000)	The analysis was based on the use of probabilistic duration modeling techniques. The hazard function was used to assess reliability of pavement sections.	This study is useful in applying the probabilistic approach into PMS.
Joint Estimation Approach in Estimating Performance Indices	(Prozzi 2004)	Pavement performance index models were developed from the combination of both experimental and field data. Use of the joint estimation approach for the development of pavement performance models was found in this study. A riding quality model based on serviceability consideration was also developed. The original model parameters were re-estimated by applying joint estimation with the incorporation of field data set. The error of the new model was found as half of the existing model.	This study is useful to overcome the limitations of the OLS approach.
Estimation of Performance Index	(Yu 2003)	A 'linear mixed effects model' was developed to predict future pavement conditions. This model was developed by a weighted combination of the average deterioration trend and the past pavement conditions.	This model was developed based on a weighted combination of the average deterioration. However, the precise prediction model requires incorporation of the effects of traffic and materials.
Estimation of Performance Index	(Prozzi 2003)	Non-linear models were developed for KPIs for realistic prediction of pavement conditions. The KPI model was developed considering traffic characteristics, pavement structural properties, and environmental conditions.	This study is useful for estimating performance index models to incorporate the effect of traffic characteristics, pavement structural properties and environmental conditions.

Relevant Research Area	**Author/ Authors**	**Research Summary**	**Remarks**
Effect of KPI Model in LCCA	(Madanat 2002)	Effect of KPI model accuracy was investigated on optimal design and life cycle costs by using a regression model and probabilistic model.	This study is useful to investigate the impact of KPI model accuracy on LCCA.
Effectiveness of KPI Model Estimation	(Archilla 2001)	Effectiveness of the estimation of rutting models was investigated by combined estimation.	This study will also help in applying combined estimation.
Effectiveness of KPI Model Estimation	(Chu 2008)	Effect of different statistical assumptions and estimation techniques of KPI models on predictive capabilities were explored by using AASHO road test data.	This study will help in investigating statistical assumptions.
Estimation of Performance Index	(Tighe 2008)	The DMI model was evaluated by using automated distress evaluation data in Southern Ontario, Canada. The randomized block design (RBD) approach was used for the hypothesis test in this study. A hypothesis test was performed to determine the differences in the DMI model on the basis of automated evaluation data.	This study is useful for estimating performance index in PMS.
Probabilistic Approach in Estimating Performance Index	(Molenaar 2011).	Probabilistic duration modeling techniques were used in the investigation of performance measures during road design and construction	This study is useful in applying probabilistic approach in estimating the performance index,
Joint Estimation Approach	(Zellner 1962) (Zellner 2006)	Instead of the OLS approach, Zellner formulated the SUR estimator to account for contemporaneous correlations among multiple dependent variables in a suit of regression models. This method uses a set of equations, which are contemporaneously correlated and share a common random error structure with non-zero covariance. The SUR method estimates the parameters of all equations simultaneously.	This study is very useful in applying joint estimation approach in estimation.
Application of SUR approach in Estimating KPI model	(Prozzi 2008)	Recently, the SUR approach was applied to capture the deterioration process of pavement performance. This study applied the SUR approach to the simultaneous estimation of pavement performance	Application of SUR proved accurate estimates when unobserved factors are correlated in joint estimation.

Relevant Research Area	Author/ Authors	Research Summary	Remarks
		deterioration models. The deterioration of two major indicators, IRI and rut depth, were investigated. The results showed improved performance characterization and more accurate forecasting for IRI and rut depth.	
Application of M-E Approach: Local Calibration of Rutting	(Hoegh 2010)	Conducted local calibration of rutting model using time history rutting performance data for pavement sections at the Minnesota Department of Transportation. In this study, detailed comparison of the predicted total rutting, asphalt layer rutting, and measured rutting is carried out.	The results show that the locally calibrated models are less biased than the predictions using the globally calibrated rutting models.
Application of M-E Approach: Local Calibration of Cracking	(Hall 2010)	Conducted the initial local calibration of flexible pavement models in the MEPDG for Arkansas. It is found that for the current MEPDG, predicted distresses did not accurately reflect measured distresses, particularly for longitudinal and transverse cracking. Calibration coefficients are optimized for the alligator cracking and longitudinal cracking models minimizing the sum of standard error.	Due to the lack of measured transverse cracking, the transverse cracking model was not calibrated.
Application of M-E Approach: Local Calibration of Longitudinal Cracking, Thermal Cracking and IRI	(Siraj 2009)	Verified the accuracy of the predicted performance from the MEPDG software for the state of New Jersey for Level 2 and Level 3 inputs. In this verification, nine LTPP and sixteen non-LTPP sections in the state of New Jersey are evaluated. The measured longitudinal cracking, thermal cracking and roughness (IRI) are found statistically similar to the predicted values.	The prediction of MEPDG software 1.0 was not accurate for IRI.
Application of M-E Approach: Local Calibration of MEPDG Distresses	(Velasquez 2009)	Analyzed the performance prediction and evaluated of different types of flexible and rigid pavements for local conditions. Performance prediction models are evaluated and recalibrated to reduce bias and error for Minnesota conditions.	The use of the longitudinal cracking model is not recommended for adaptation since the IRI model could not be locally calibrated.

Relevant Research Area	**Author/ Authors**	**Research Summary**	**Remarks**
Application of M-E Approach: Local Calibration of MEPDG Crackings	(Moulthrop 2007)	Calibrated MEPDG distress transfer functions for flexible and semi-rigid pavements of Montana. The results show that fatigue cracking (bottom up) model is reasonable, a local calibration factor for predicting thermal cracking is developed.	For the top-down fatigue cracking model, no consistent trend in the predictions is identified to reduce bias and standard error.
LCCA for Cost-Effective M&R Schedules based on MEPDG	(Mandapaka 2012)	Evaluated and selected an optimal M&R strategy for a flexible pavement road section by integrating LCCA and California Mechanistic-Empirical (CalM-E) design procedures.	It is found that this study is carried out based on one road section for selected distresses of MEPDG. Overall performance of KPI is not considered for LCCA, which is generally used for M&R schedules.
Benefit Costs Analysis for Network Level Optimization	(De la Graza 2010)	Developed decision making tool for network-level optimization for pavement maintenance programming problems through linear programming. This decision making tool presents alternative highway maintenance strategies through an automated process in Microsoft Excel.	This study focuses on the budget allocation process, depending on the condition of lane-mile.
LCCA for Preventive Maintenance	(Labi 2005)	Investigated the cost-effectiveness of various levels of life cycle preventive maintenance for three asphaltic concrete pavement functional class families. This study estimated cost-effectiveness using existing performance models, performance jump models and cost models for each maintenance treatment type.	The performance jump models were not based on M-E analysis.
Integrated Dynamic Performance Prediction for M&R Optimization	(Ningyuan 2005)	This optimization model considered cost-effectiveness based on multi-year priority programming. This study selected M& R strategy based on predicted improved PCI value. Improvement of PCI value is predicted based on historical records of that treatment type.	The local traffic, materials, weather and other existing factors might have significant influence on predicted pavement serviceability. MEPDG analysis will improve this prediction of pavement condition.
Variability into Pavement Performance Models and LCCA	(Whiteley 2005)	Considered the variability associated with the discount rate and incorporated all associated variability into the LCCA of Canadian long-term pavement performance. Distributions for service life and life cycle costs were developed by using both normal and	In this study the variability factors, such as overlay thickness variation, total prior cracking variation and accumulated ESALs after eight years variation, are considered into LCCA.

Relevant Research Area	Author/ Authors	Research Summary	Remarks
		log-normal distributions for overlay thickness. These LCCA differences are then used as a basis for establishing pay factors.	

2.5 Research Gaps and Opportunities for Innovation

The literature review indicates that almost all the cost-effective M&R schedules are developed by different agencies generally based on a subjective performance index.

In any PMS, in predicting deterioration of pavement conditions, a generalized sigmoidal equation, irrespective of traffic and materials, is followed. Furthermore, predicted performance jump for any treatment is estimated generally based on historical record or engineering judgement. However, this jump depends on material types of the treatments applied. Similarly, the deterioration of pavement over time depends on many local and existing factors, such as traffic, materials, pavement structure and existing conditions of the respective road section. Therefore, there is a gap in assessing the pavement conditions by the KPI models. However, M-E analysis will predict the distress by considering local road conditions, which will in turn improve the prediction of pavement conditions.

Although agencies employ different sectioning to evaluate the field performance of pavement, there is a gap in understanding the impact of section lengths on the performance evaluation.

Although recent research has contributed significantly to developing the KPI models based on the factors affecting the performance, these are not estimated jointly. Moreover, recently, application of SUR proved accurate estimates when unobserved factors are correlated.

Many recent research works have contributed significantly to investigating LCCA to identify a cost-effective pavement M&R strategy. However, the maintenance decision is made by considering the trigger value of the selected performance index. Therefore, improvement in the performance index and its application into the LCCA will ensure more precise identification of a cost-effective M&R strategy.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

The goal of this research is to develop an efficient road M&R schedule by using the M-E approach and incorporating performance prediction models of KPIs that consider the impact of traffic and materials.

Based on the literature review, it is evident that the predicted improvement in performance in terms of the indices after any treatment is set based on engineering experiences. Moreover, the remaining service life of pavement is estimated from the predicted deterioration of the overall condition by considering only the effect of age notwithstanding the effect of traffic or materials. This deterioration of the performance index (in terms of PCI, RCI and DMI) is calculated as a deduced value from the initial condition. This deduced value may reflect traffic levels, even though traffic is not directly considered. It is observed that the M-E approach is followed by many highway agencies to predict distresses in a precise way by incorporating the effect of local traffic, materials and environmental conditions. Consequently, the incorporation of the M-E approach in assessing the overall condition of pavement, rather than only applying engineering judgement, is reasonable. The research framework is developed in this chapter with a goal to incorporate these improvements in assessing pavement performance.

3.2 Limitations in Assessing the Overall Pavement Condition

The relevant literature review and the existing practice of the performance index in a PMS confirm that there are limitations in assessing the overall pavement condition. As discussed that the predicted improvement in performance is estimated generally based on engineering experiences The estimated performance improvement and the expected life span used for typical pavement rehabilitation activities on Ontario highways are listed in Table 3.1 (Ningyuan 2001).

The remaining service life of pavement is estimated from the predicted deterioration of the overall condition by considering only the effect of age notwithstanding the effect of traffic or materials. The future deteriorated condition is calculated (in terms of PCI, RCI and of DMI) following a general equation of sigmoidal form, with different model coefficients (Ningyuan 2001). The future performance of highways is estimated by the following equation:

$$P = P_0 - 2e^{(a-bc^t)} \tag{3.1}$$

Where,
P = Performance Index, RCI or DMI
Po = P at Age o
t = Log $_e$(1/Age)
a,b,c = Model Parameters

Similarly, in municipal roads, a deduced value is estimated and the future condition is estimated by deducting the deduced value from the initial condition. This deduced value is estimated by the following equation (ARA 2006):

$$DV = 10^{(a+b\times Log\%)} \tag{3.2}$$

Where,
a and b = User-Determined Constants
% = Percentage Area of the Road Affected by Distress

The parameters of these equations are generally estimated from the historical performance record of the specific pavement types.

Table 3.1: Performance Improvements on KPIs for Typical Pavement Rehabilitation Activities on Ontario Highways

Rehabilitation Alternative for Flexible Pavements	Expected Life	Performance Index Increase after Treatment		
		PCI	RCI	DMI
Hot In-Place Recycling	10.5	90	8.5	9
Cold In-Place Recycling	12.5	90	8.5	9
1 Lift Hot Mix Overlay	7	85	8	9
2 Lifts Hot Mix Overlay	10	90	9	9
Mill 1 Lift and 1 Lift Hot Mix Overlay	8.5	90	8.5	9
Full Depth Removal/Reclamation and 1+ Lifts Hot Mix Overlay	13.5	95	9.5	10
White Topping	11	90	9	9
Reconstruction to Flexible Pavement	16	95	9.5	10
Reclamation, 2 Lifts Hot Mix Overlay	12.5	90	9	9
Full Depth Removal/Mill Reclamation	12.5	90	9	9
Pulverize, Grading, Double Surface Treatment	11	85	9.5	9.5

The improvement in performance may vary depending on the respective materials. Moreover, the deterioration of the pavement conditions over time will also be different, depending on the traffic and associated responses of the pavement materials or structure. Figure 3.1 presents how the pavement performance deterioration is estimated over time.

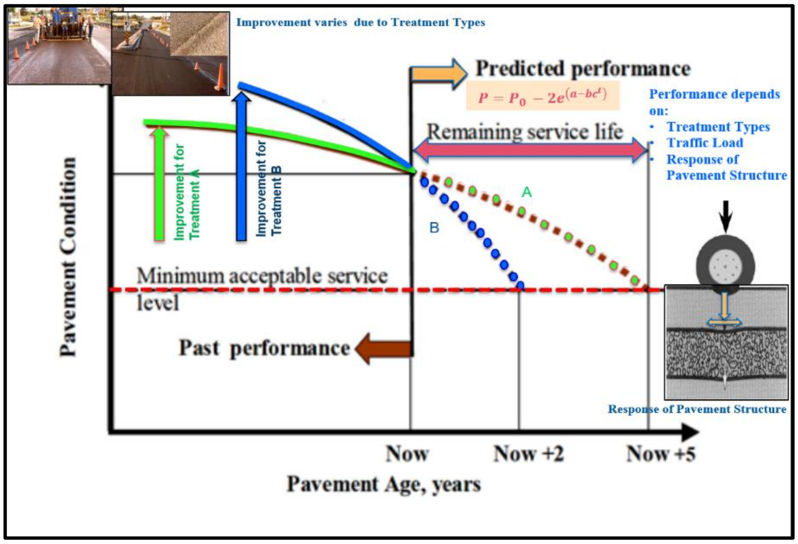


Figure 3.1: Pavement Performance for different Treatments (modified from TAC 2013)

However, the performance prediction by only engineering judgement or historical records may sometimes mislead the pavement engineers and managers to identify the correct treatment and correct time to apply it. Therefore, there is a gap for improvement in assessing the overall pavement conditions.

3.3 Research Methodology Framework

The literature review, recent research and current adaptation of MEPDG-based pavement design validates the precise prediction of distresses by incorporating the effect of local traffic, environmental conditions and materials. Subsequently, this justifies the need to incorporate the M-E approach to overcome the aforementioned limitations of engineering judgement in assessing the overall pavement conditions. The research framework is finally developed with a goal to incorporate these improvements in assessing the overall performance of pavement.

Although the final objective of the research is to develop cost-effective pavement maintenance and rehabilitation strategies, the precise assessment of pavement is a significant part to achieve it. Overcoming the limitations in estimating the improvement for specific treatments and the respective deterioration patterns are key parts of precise performance assessment of pavement. The method of pavement performance evaluation in managing PMS also has a significant effect. An accurate location reference system is necessary for managing pavement evaluations and maintenance. For that reason, the impact of section lengths on performance evaluations and maintenance decisions will be investigated. Moreover, the method of estimating performance indices will be further investigated to identify the improvement requirements. From the literature review, it is observed that the performance indices to assess the overall condition are estimated by using the OLS approach. However, OLS may be inefficient if unobserved factors influencing individual KPIs are correlated with each other. For this reason, this research proposes the use of the 'Seemingly Unrelated Regression (SUR) method instead.

As discussed in the previous section, the M-E approach will be used to overcome the aforementioned limitations of engineering judgement in assessing the overall pavement condition. However, before applying the M-E approach, it is important to identify the requirements of the accuracy level of inputs for precise prediction. For this reason, a sensitivity analysis will be carried out for the inputs of MEPDG distresses based on an experimental design to identify the requirements of the accuracy level of inputs. The distresses predicted by the M-E approach will be compared to field-evaluated performance to identify the requirement of local calibration of the MEPDG-based prediction models. A preliminary local calibration will be carried out to improve the accuracy and precision of the models. Since the research is focused on identifying cost-effective pavement M&R activities, a clustering analysis will be conducted based on the material types. This study did not calculate the optimal local calibration coefficients in the transfer models, however, the preliminary local calibration of the predicted value will help ensure precise prediction.

It is discussed that the prediction models of the performance indices are developed based on historical performance record of pavements. However, the deterioration of pavement is affected by the site-specific traffic, local environment and properties of materials. As a result, the M-E approach will be incorporated in assessing the overall condition of pavement to overcome the limitations of engineering judgement. The prediction models will be developed to assess the overall condition by considering all local variables affecting the pavement, which include site-specific traffic, local environment, properties of materials and existing pavement structure. Moreover, the deterioration of the overall condition varies significantly depending on the characteristics of traffic and material types. For this reason, the deterioration model will be estimated for different levels of AADT to recognize the influence of the difference in traffic and properties of materials. The time required for maintenance will also be estimated based on a trigger value of an index. However, the pavement may fail due to any specific reason before reaching the trigger value of maintenance. For this reason, the probability of failure will be investigated by a probabilistic approach. Finally, a LCCA will be carried out for a period of 40 years for alternate overlay options based on the deterioration models of the overall pavement condition. The steps of this study's research method are shown in Figure 3.2.

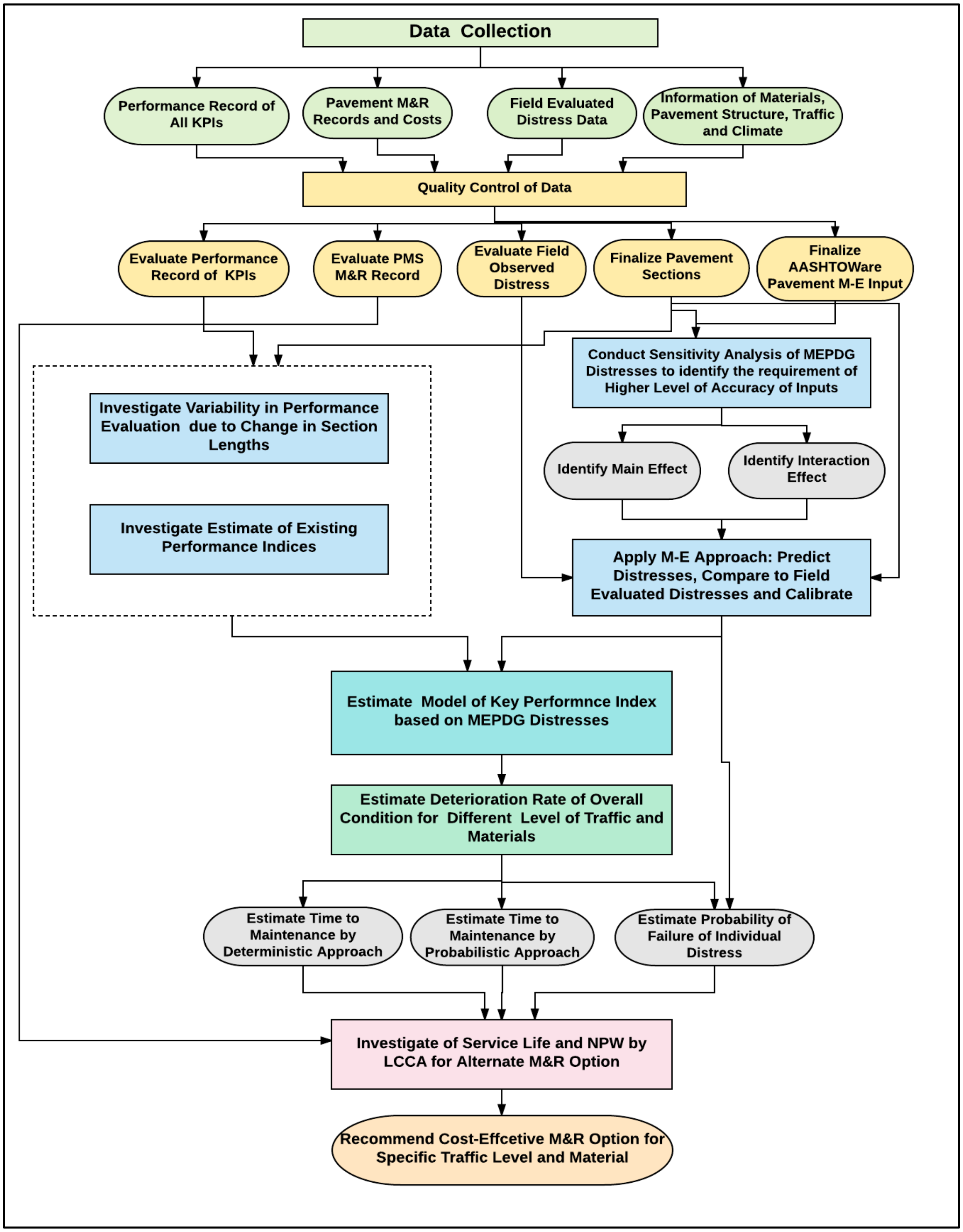


Figure 3.2: Research Methodology

3.3.1 Data Collection

This study will use pavement performance data of Ontario highways recorded in the MTO PMS database. The PMS for Ontario highways was first established in the 1980s. At that time, the computers were not cost-effective and the pavement M&R was based on qualitative engineering experience (Olivier 2010). Since then, the MTO's PMS has undergone a number of enhancements and releases. Presently, it uses a second generation PMS, also known as PMS-2 (Ningyuan 2001, and Ningyuan 2004). PMS-2 maintains pavement performance, maintenance and operational records related to 16,500 center-line kilometers of freeways, collectors and arterial and local roads (Ningyuan 2008). PMS-2 also collects detailed annual records of cracking and distresses.

Since this research focuses on the development of performance prediction models and maintenance and rehabilitation strategies, all records of annual performance (crackings and distresses), KPI performance (PCI, DMI, RCI, rut depth and IRI) and M&R performance are collected.

For predicting the distresses, the MEPDG software AASHTOWare Pavement M-E will be used. The three major categories of input variables for the prediction of pavement distresses are required. They are: traffic data, climate data, and properties of layers and materials. Hierarchical input data of these three major categories will be collected for all selected road sections.

Therefore, data collection processes mainly involve collecting the information of the following four components:

- (i) Pavement performance records of all KPIs (PCI, DMI, RCI, rut depth and IRI)
- (ii) Pavement M&R records, including type and costs of treatments
- (iii) Field-evaluated pavement distress records (cracking and distresses)
- (iv) Input data for AASHTOWare Pavement M-E software (traffic, weather and materials)

The uninterrupted service life, which began after new construction or overlay design and ended before applying any other treatment (if improvement in performance index is observed due to that treatment, which may not reflect the improvement due to minor treatment), is considered as one 'performance cycle' in this research. The word 'performance cycle' will be used throughout the study to define this uninterrupted pavement service life between two consecutive treatments. This performance cycle will be used as the respective service life during distress predictions based on the M-E approach.

Various pieces of information are required to conduct these studies in different steps. The road sections are selected based on the available information required for analysis. Table 3.2 lists the number of highway sections selected in each step of this research.

Table 3.2: Selected Highway Sections

Investigation Step	No. of Highways Sections	Type of Highway	Performance Cycles	Other
Investigation of Variability in Performance Evaluation Due to Change in Section Lengths	27 highway segments from Ontario's Central Zone, which consist of 3,451 50m sections, 346 500m sections, 152 1,000m sections and 15 10,000m sections.	Freeways	Only for the year of 2013	
Estimation Analysis of Existing Performance Index	61 road segments from major highway networks	Freeways and Arterials	158 Performance Cycles	
Application of M-E Approach: Sensitivity Analysis	N/A[1]	Freeways and Arterials	N/A	For main effect: 171 experimental sets For interaction effect: 58 experimental sets
Application of M-E Approach: Prediction, Comparison and Verification	128 highway sections from 19 highways	Freeways and Arterials	176 Performance Cycles (1530 Performance Years)	
Estimation of Model and Deterioration of Performance Index	128 highway sections from 19 highways	Freeways and Arterials	176 Performance Cycles	
LCCA	A typical highway section			

3.3.1.1 Pavement Performance Record of KPIs

Over the past 30 years, several evaluation indices were recorded in the MTO PMS-2 to obtain rational maintenance and rehabilitation decisions, such as IRI, PCI, DMI, PCR and RCI (Ningyuan 2001). These KPIs are calculated from the field-evaluated distresses based on the weighting given by the agencies. The annual records of these KPIs are collected.

The performance records of PCI, IRI and rut depth are collected for 2013 to investigate the variability in performance evaluations due to changes in section lengths. For this investigation, a total of four types of section lengths are observed. These are 50 m, 500 m, 1,000m and 10,000m sections.

In analysing the estimate of the existing performance index, annual records of KPIs, including rut depth, are collected for 61 highway sections. For estimating the model and deterioration rate of KPIs, annual records of IRI, PCI and DMI are collected for 128 highway sections.

[1] N/A= Not applicable

3.3.1.2 Pavement M&R Records

Pavement M&R records are required to conduct LCCA and also to define uninterrupted performance cycles for road sections. For the selected 128 highway sections, historical M&R activities, treatment types, construction periods, routine maintenance activities and layer structure information, including unit costs of each treatment option, are collected.

3.3.1.3 Field Pavement Distress Data

For analyzing the estimate of the existing performance index, annual cracking and distress evaluations are collected for 61 highway sections. In comparing the field-evaluated distress to predicted distress by the M-E approach, annual field evaluations for IRI, rut depth, thermal cracking, bottom-up fatigue cracking and top-down fatigue cracking are collected for 128 highway sections.

3.3.1.4 Hierarchical Input for AASHTOWare Pavement M-E

For predicting the MEPDG distresses, the recent version of MEPDG software AASHTOWare Pavement M-E (version-2) will be used. The input data required for the AASHTOWare Pavement M-E analysis refer to traffic, climate, pavement structure and material properties. For each pavement section, the inputs will be collected following the recommendations of the MEPDG Manual of Practice (AASHTO 2008). The AASHTOWare Pavement M-E software allows input data at three level of accuracy (AASHTO 2014), as described below.

Level 1: Input parameters are the most accurate. Generally, site-specific or site-measured and laboratory data and results of field testing are considered as Level 1 input. For example, laboratory test values of dynamic modulus and nonlinear resilient modulus are considered as Level 1 for material properties. For traffic, site-specific traffic data, such as AADTT, lane numbers, traffic growth factors, are considered as Level 1 input.

Level 2: Generally, the input parameters estimated from mathematical correlations or regression equations, or calculations from other site specific data, are considered as Level 2 input. For example, resilient modulus estimated from CBR values are considered as Level 2 input.

Level 3: Input parameters are the least accurate. They are normally default values or based on best estimates. Generally, national level or regional level values are used.

Based on the results of the proposed sensitivity analysis, the required accuracy level of input will be identified and input will be collected accordingly.

General Information

General information for the selected road sections, including design life (in terms of performance cycles), existing pavement constructions year, pavement overlay construction year, traffic open date and new construction and rehabilitation history will be collected for all 128 highway sections. The design life will be considered as the performance cycle length of the pavement section for that specific treatment.

Traffic Data

For the selected 128 highway sections, traffic information, including traffic volume adjustment factors and axle-load distribution factors are collected. The M-E analysis uses the concept of load spectra for characterizing traffic where each axle type (e.g., single, tandem and tridem) is divided into a series of load ranges. The vehicle class distributions, daily traffic volumes and axle-load distributions are collected for each road section.

A web-based mapping program called 'iCorridor' developed by the MTO, is used for the required traffic information. The 'iCorridor' provides site-specific traffic information, which are mainly Level 1 input, for each highway section. Although the traffic stream information is measured directly for specific highways, the section (selected for this study) specific traffic information is not always available. For this reason the traffic stream information available over the entire highway is used for some of the sections which do not have site specific information. Figure 3.3 shows the web-based map program of 'iCorridor'. If traffic data is insufficient within the selected section, default values for Southern or Northern Ontario will be used as Level 2 input.

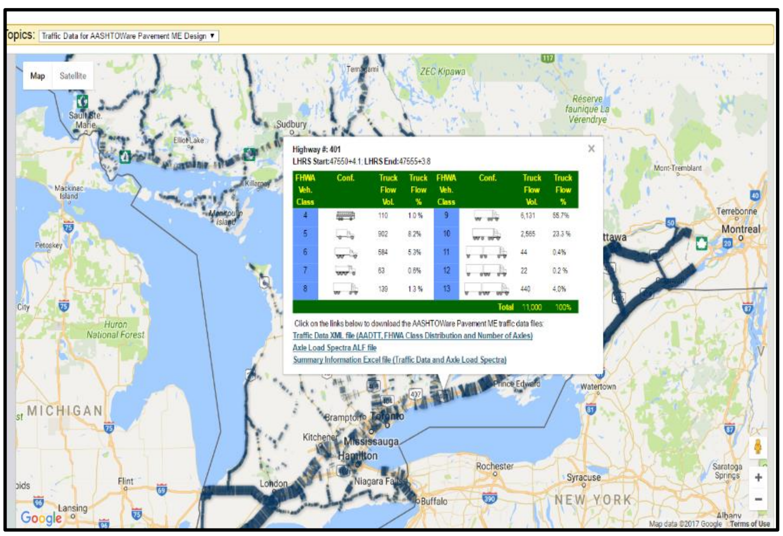


Figure 3.3: Web based Map of 'iCorridor'

Climate Data

For the M-E analysis, the historical records of daily and seasonal fluctuations in the moisture and temperature profiles, ground water tables, precipitation, infiltration, freeze-thaw cycles and other external factors are required.

The climate information available from Environment Canada is already processed for use in AASHTOWare Pavement M-E Design. Currently, there are a total of 34 weather stations in Ontario, which are available in the AASHTOware software. Figure 3.4 shows the location of Ontario climate stations. The geographical location information of 128 road sections in terms of longitude, latitude and elevation are collected.

For a specific location, where no weather data is available, the Integrated Climatic Model (ICM) is used to create a virtual weather station by incorporating the climatic data from neighboring weather stations.

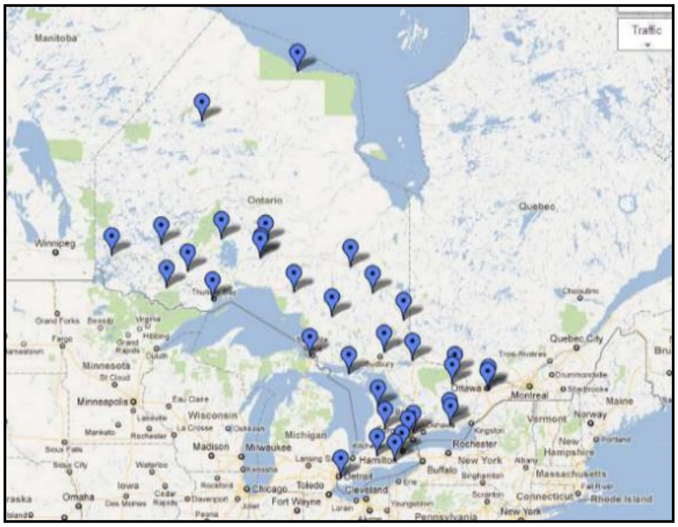


Figure 3.4: Location of Ontario Climate Stations

Material Properties

The material properties are collected for 176 performance cycles of 128 highway sections. The AASHTOWare Pavement M-E requires the use of material properties of the pavement layers to create a mechanistic analysis of the pavement responses. If any properties are not found or specified, Ontario Provincial Standard Specification (OPSS) and Ontario's Default Parameters for AASHTOWare Pavement M-E Design are followed for default values (MTO 2012).

3.3.2 Quality Control of Data

The investigations will be conducted based on the collected data, which is mainly recorded in the MTO PMS-2 and specific project documents. This research uses the historical data recorded in the database from the construction year to 2013. Many of the highway sections were constructed in 1980s. Previously, the pavement conditions were evaluated by the multiple raters' by following the manual survey. Moreover, in the database, the value of performance indices are not consistent with M&R activities. Therefore, the quality control of the inconsistent data is important for accurate analysis. The quality of the data is controlled by following statistical methods and graphical comparison.

3.3.2.1 Performance Record of KPIs

It is observed that the performance improvement of KPIs (DMI, RCI, PCI and IRI) recorded in the database are not always consistent with the M&R year. Since the field evaluation might not always be carried out subsequent to maintenance or rehabilitation, this inconsistency is adjusted following the year of the M&R record. In PMS-2, the IRI values are not recorded before 1997. The IRI values for the road sections can be estimated starting in 1997 or prior to 1997 using the following equation (MTO 2007):

$$RCI = Max\ (0, Min\ (10, 8.5 - 3.02 \times ln\ (IRI))) \tag{3.3}$$

The performance conditions of pavement for DMI, RCI, PCI and IRI are plotted against the service life for all pavement sections to observe its consistency with M&R records. The deterioration in DMI, RCI and PCI with an increasing value in IRI are observed. If there is any improvement in DMI, RCI and PCI, it is considered that a minor and major M&R occurred. The pavement performance is observed in this way from the construction year to 2013. From this comparison, the performance cycle is also identified, in years, from one treatment to another. For example, the performance of Highway 7 (west bound, location Km 553.172 to 556.072) is observed from the construction year 1986 to 2010. The performance curves of PCI DMI, RCI and IRI are plotted in Figure 3.5.

In Figure 3.5, the deterioration patterns of all KPIs are found as consistent. It is observed that in 1998, there was slight improvement in pavement conditions. Considering that a treatment was applied that year and the first performance cycle ended in 1997 (a cycle of 12 years), no M&R was recorded in PMS-2 for 1998. In the 2003 and 2004, there was improvement. For this reason, a performance cycle consisting of minimum 4 years is considered so that a smooth curve of performance curve can be drawn. For this reason, if a performance cycle is found consisting of less than 4 years, that cycle is dropped from the experimental design. For this reason, 2003 is removed from the analysis and another performance cycle from 2004 to 2010 (a performance cycle of 7 years) is considered instead. All pavement sections are assigned to their corresponding cycles in this way.

3.3.2.2 Pavement M&R Records

The M&R records are made consistent with historical KPI records for 176 performance cycles by following the previous section 3.3.2.1.

3.3.2.3 Field-Evaluated Distress Data

The field-evaluated distress of 128 highway sections is observed for 1,530 performance years. The evaluated yearly distresses confirm that the highways are deteriorating consistently over time. This study will finally estimate the performance deterioration curve of pavement condition based on different traffic levels and materials types. The road sections are finalized after screening the data and selecting the perfornace cycles.

3.3.2.5 Input Data for AASHTOWare Pavement M-E Software

It would be the best option if all inputs were of the highest accuracy (Level 1). However, it may be inefficient to put effort in obtaining Level 1 for all inputs. For this reason, a sensitivity analysis will be carried out to identify important input, which has significant effect on MEPDG distresses.

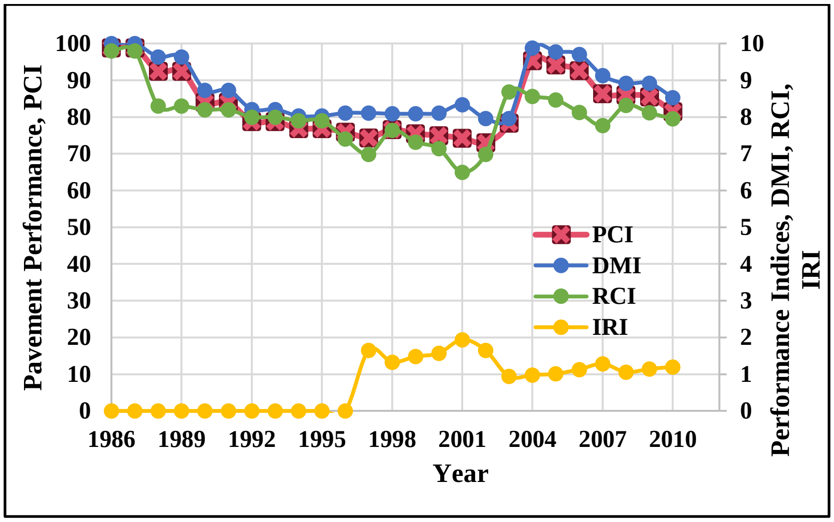


Figure 3.5: Comparison of Pavement Performance in Terms of DMI, RCI, IRI and PCI of Highway-7W

3.3.3 Investigation of Variability in Performance Evaluation

As discussed, the precise assessment of the overall pavement conditions is a key part in achieving the research goal of incorporating improvement in existing use of KPIs. For this reason, precise performance evaluations are necessary and require an accurate location reference systems. Moreover, in Ontario highways, pavement sections are predefined for assessment. The section lengths range from 50m to 50,000m. For this reason, the effect of section lengths on performance evaluations and corresponding maintenance decisions is to be investigated.

Although PCI for Ontario highways is generally used as an overall index, rut depth and IRI are used as KPIs to identify the trigger value of maintenance decisions. The performance of PCI, IRI and rut depth will be investigated for different section lengths (50m, 500m, 1,000m and 10,000m). A statistical analysis will be conducted in three steps. Rut depth will be used to investigate the impact of section lengths. The effect on overall conditions of road segments will be investigated by comparing the PCI and IRI for the selected section lengths.

After considering the variation due to changes in section lengths in the evaluated performance of the KPIs, the impact on maintenance decisions will also be investigated. A Monte Carlo simulation will be carried out by varying the section lengths. With this simulation, corresponding variations in the estimated probability of work will be investigated.

3.3.4 Analysis of Estimate of Existing Performance Index

The method of estimating performance indices will be further investigated to identify the improvement requirements in estimation. It is observed that in many PMS, KPIs are generally estimated by using the OLS approach. However, the OLS may be inefficient if unobserved factors influencing individual KPIs are correlated with each other. For this reason, an approach called the ‘Seemingly Unrelated Regression (SUR)' method will be used instead.

The severity and extent of all distresses (listed in Chapter 5) that have significant effect on the overall condition of pavement will be considered as independent variables for estimating KPI models.

3.3.5 Application of ME-Approach: Sensitivity Analysis

Since the MEPDG analysis considers three-level hierarchical inputs to predict performance, these inputs with different levels of accuracy may have a significant impact on performance predictions. For this reason, a sensitivity analysis will be carried out to identify the accuracy-level requirements for precise prediction. For the statistical validity of investigations, an experimental design-based approach will be used.

For the main effect, local sensitivity will be carried out and for interaction effect, experimental design will be formed based on a random combination of variables.

3.3.6 Application of M-E Approach: Prediction, Comparison and Verification

The requirement to incorporate the M-E approach to overcome the limitation of engineering judgement in the PMS is discussed in the research methodology framework. The distresses will be predicted by the M-E approach for 176 performance cycles. These predicted distresses will be compared to field-evaluated performance to identify the local calibration requirements of the MEPDG-based prediction models. A preliminary local calibration will be carried out to improve the accuracy and precision of the models by a cluster analysis based on the type of materials.

3.3.7 Developing Prediction Models for Assessing Overall Condition of Pavement

The prediction model will be developed by using a regression approach that considers the distresses predicted by the M-E approach. Since the deterioration of pavement is actually affected by site-specific traffic, local environment and material properties, the effect of these variables is to be incorporated in predicting the pavement's overall deterioration in a precise way. For this reason, the overall condition index model will be estimated from the M-E based predicted distresses. It is evident that the pavement performance curve will be different for different traffic levels and material types. To recognise these variations, the pavement performance deterioration model (parameters of equation 3.1) will also be estimated for different categories of traffic level and material type. The time required for maintenance will also be estimated for these categories to ensure the appropriate time for treatment. The probability of failure will also be investigated by a probabilistic approach, considering both pavement overall condition and individual distress.

3.3.8 Investigation of LCCA to Recommend a Cost-Effective M&R Strategy

In a PMS, the identification of cost-effective M&R treatments is challenging. A cost-effective pavement M&R approach is needed to allocate the PMS budget in an efficient way. For this purpose, a LCCA will be conducted by following the estimated deterioration model discussed in the previous section. Since the deterioration rate of the overall condition is considered to vary depending on the type of materials and AADT levels, this variation will be taken into account for predicting the remaining service life. This will confirm that the LCCA is precise and that the identification of the corresponding cost-effective M&R will be precise too.

In this study, the cost-effective M&R strategy refers to the M&R option identified from the LCCA that has the maximum service life and minimum treatment costs in terms of NPW. This study considers only resurfacing or overlay activities with different types of materials instead of other maintenance activities. Since M-E approach can analyse only overlay M&R activities, and can predict distresses based on the applied overlay layer materials, this study compares only different types of overlay materials instead of all M&R activities.

3.4 Summary of Research Methodology

The research methodology was developed with a goal to incorporate the improvements in assessing the overall performance of pavement.

The KPIs used in the PMS do not incorporate local factors, such as pavement type, traffic, weather and road-specific materials. The predicted improvement of KPIs after any treatment are set based on the experiences and the deterioration patterns of KPIs calculated based on empirical relationships. The proposed KPIs based on the M-E analysis will overcome these limitations. Although the final objective of the research is to develop a cost-effective pavement M&R strategy, the precise assessment of pavement will achieve the goal. An investigation of variability due to changes in section length in the evaluation of pavement performance is proposed by incorporating an accurate location reference system. The SUR method is proposed to identify the improvement requirements in the estimate of the existing KPI model. To recognize the influence, prediction models will be estimated by considering the characteristics of traffic and material types. A probabilistic approach is also proposed to predict the probability of failure of pavement based on overall condition and individual distress as well. Finally, a LCCA will be carried out for a period of 40 years for alternate overlay options by incorporating the variation for different levels of traffic and material types. The research will be conducted in subsequent chapters following the proposed methodology outlined in this chapter.

CHAPTER 4
ANALYSIS OF VARIABILITY IN PAVEMENT PERFORMANCE EVALUATION

In PMS, the performance evaluation indices and prediction methods are important aspects in assessing the overall pavement condition. Therefore, an accurate location reference system is necessary to manage pavement evaluations and maintenance. The length of the pavement section selected for evaluation may also have a significant impact on the assessment of condition irrespective of the type of performance indices. This chapter investigates the variability in pavement performance evaluation and maintenance decisions due to change in pavement section lengths. It considers rut depth, PCI and IRI as performance indices.

The results presented in this chapter are published in the Transportation Research Record (TRR): Journal of the Transportation Research Board (TRB) 2016 (Jannat 2016). Part of this chapter was also presented at the Eighth International Conference on Maintenance and Rehabilitation of Pavement in 2016 (Jannat 2016).

4.1 Introduction

Evaluation of pavement performance is sophisticated due to the complexity of factors and associated interactions that influence pavement performance. An effective PMS is possible only when pavement performance is evaluated accurately and efficiently. The PMS analysis results vary significantly with the length of each pavement section and the selected performance indicators used for the condition assessment.

Pavement sections for assessment are predefined for all individual provincial highways managed by the MTO and the summaries of the pavement condition data and evaluation results are reported based on these predefined pavement sections. Typical lengths of such sections range from 50m to 50,000m. Although the long sections are homogenous or classified by pavement structure and geographic locations, they do not represent homogeneous performance conditions, including rut depth, IRI and PCI. For this reason, this study focuses on investigating the influences of section length on performance evaluation generated by PMS-2. The study also investigates the impact of section lengths on subsequent maintenance management and decisions.

The implications of section lengths are investigated in two steps: first, on performance monitoring and second, on maintenance decisions. This investigation uses data from the MTO PMS-2 to evaluate the impact of varying sections lengths on overall outcomes of the analysis. For empirical investigations, pavement performance data of Ontario's Central Zone highway network is used.

4.2 Existing KPIs Used on Ontario Highways

As discussed in the previous chapter, different KPIs are used in pavement evaluations for Ontario highway systems. PCI is generally used as an overall condition index in pavement M&R decision trees. The decision trees use a series of logical tests to capture the decision-making process in selecting appropriate M&R treatments based on the status of KPIs (Kazmierowski 2011).

The DMI, which is a component of the PCI, is also an important index. MTO has classified the distresses into 15 categories and assigned weights to them in order to calculate DMI. The PCI is composed of two sub-indices representing DMI and IRI. In Ontario, the formula used to calculate PCI from DMI is defined as follows (MTO 2007):

For Asphalt Concrete (AC) Pavement,

$$PCI = Maximum\ value\ of\,(\,0, or\ minimum\ of\ (100, 13.75 + 9 \times\ DMI - 7.5\ \ IRI)) \tag{4.1}$$

Where,
PCI= Pavement Condition index in score
DMI= Distress Manifestation Index in score
IRI= International Roughness Index in mm/ m

Recently, Ontario highway systems are moving from a manual rating system to an automated survey regime. The formula to calculate new PCI is being changed for automated survey data and is outlined below:

$$New\ PCI = (0.7 \times\ IRI\ Scaled) + (0.2 \times DMI) + (0.1 \times Rut\ Scaled) \tag{4.2}$$

Where,
$\text{IRI Scaled} = [100\ \times \{1 - \text{IRI in mm per m}\ /5\}]$
$\text{Rut Scaled} = [100\ \times \{1 - (\text{Average Rut Depth in mm}\ \ /30\ )\}]$

4.3 Road Performance Data
As discussed in the previous section, the pavement sections for assessment are predefined for Ontario highways. The pavement condition data and evaluation results are reported based on such predefined pavement sections. For 2013, detailed rut depth and performance data is collected from Ontario's Central region for different section lengths. These section lengths are categorized in the following four groups: 50m, 500m, 1,000m and 10,000m. To evaluate the performance of a particular pavement segment, the road sections are individually surveyed. Although these sections are overlapping in one segment, they are surveyed independently so that performance can be compared.

From the available performance records of the highways, only 27 road segments from two highways, Highway 401 Eastbound and Westbound, are selected as these contain these four types of section lengths. These are listed alongside the total number of sections in Table 4.1.

Road segments with maximum available length are selected where all four types of section lengths are available for that particular segment. Finally, an experimental design is selected that contains 27 road segments (covering 172.5 km length from the Ontario Central Zone) and consists of 3451 50m sections, 346 500m sections, 152 1,000m sections and 15 10,000m sections.

4.4 Variability Analysis

The objective of this chapter is to investigate the variability in pavement performance evaluation due to changes in section length for different KPIs used in PMS. Although PCI for Ontario highways is generally used as an overall index in the pavement M&R decision tree, rut depth continues to be a major concern for Ontario's major freeways. Moreover, the PCI is calculated from the deterioration condition measured by the three components: IRI, rut depth and DMI. In this study, rut depth and IRI distresses are considered. Although, it is important to note that some agencies presently view rut depth and IRI as both distresses and overall condition indices. DMI is not considered in this study as it contains only 20% of weight in the PCI, whereas DMI consists of 15 distresses along with cracking. Analyses of all 15 types of cracking and distresses may complicate the detailed data analysis at this stage.

This study involves a statistical analysis with three steps. Rut depth is used in the first step to illustrate the impact of section lengths in understanding the condition distribution. In the second step, the impact on the overall road segment conditions is investigated by comparing the PCI and IRI for these section lengths. In the third step, the impact on maintenance decisions from variations in performance evaluations due to changes in section lengths is analysed. Figure 4.1 presents steps in assessing the variability of various performance indices.

4.4.1 Investigation of Influence of Section Lengths on Rut Depth Evaluation

Rut depth is used in the first step to illustrate the impact of section lengths in understanding the condition distribution across the network. It is evident that rutting is not a key maintenance driver in the Ontario network, but its measurements are "un-processed" compared to roughness and would therefore be more meaningful for the comparisons in this first step. However, it also is recognized that rutting significantly impacts overall road safety.

At first, probability plots are compared to identify the distribution types of rut depth values. For example, a road segment from Highway 401 Eastbound (Chainage 507,000m to 518,500m) is selected to identify the best fit distribution. Figure 4.2 presents the probability plot of rut depth for this road section. After comparing the goodness of fit, log-normal and normal distribution are found to be the best fit for rut depth distribution. Normal distribution is found as the best fit for most of the road sections and thus considered for all road sections to calculate mean, standard deviation and percentile value.

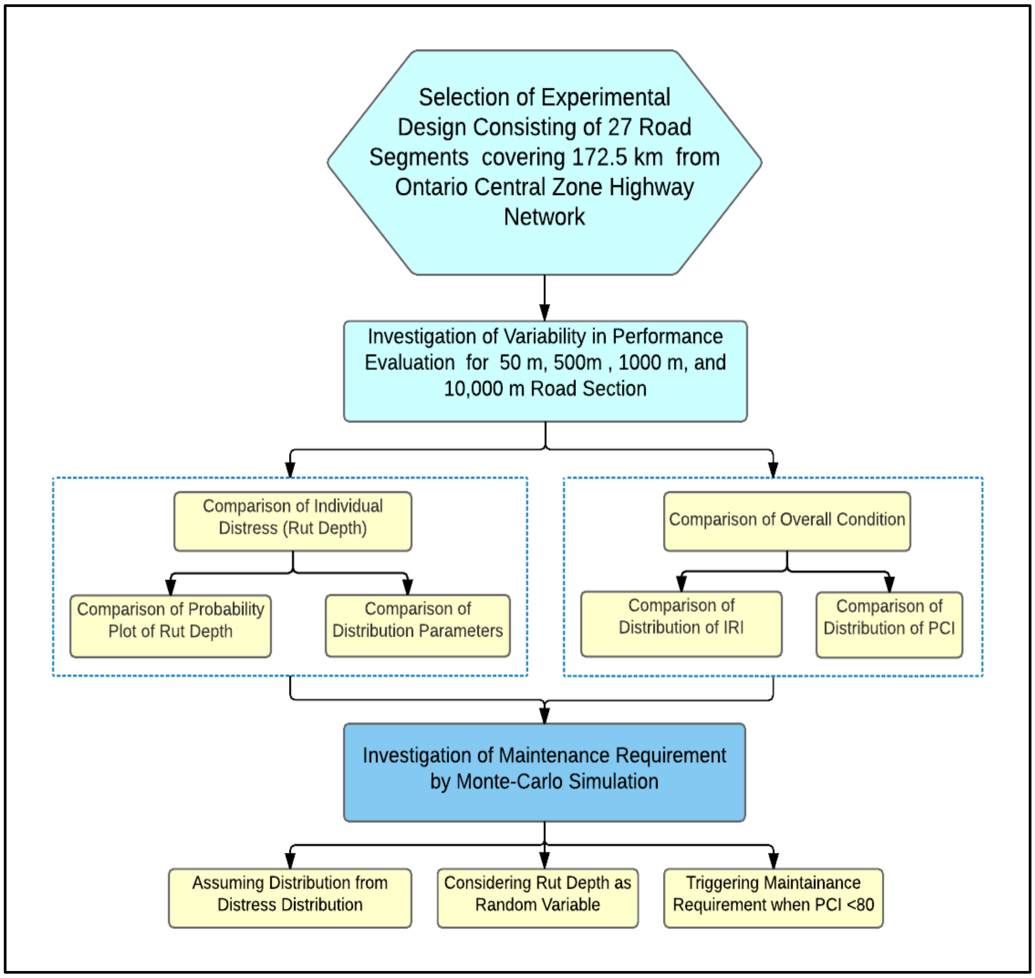


Figure 4.1: Steps in Assessing the Variability in Performance Evaluation

Table 4.1: Selected Road Segments with Four Types of Sections

Highway	Direction	Chainage of Road Segment (m)		Total Distance (m)	Section ID	Linear Highway Referencing System	No. of Total Sections based on Section Length			
		Begin	End				50m	500 m	1,000 m	10,000 m
401	East	507000	518500	11500	111390	47700	230	23	11	1
401	East	497500	506000	8500	111370	47689	170	17	8	1
401	East	378000	384000	6000	110950	47558	121	12	6	0
401	East	385000	392000	7000	110970	47560	140	14	7	0
401	East	392000	403500	11500	110990	47570	229	23	10	1
401	West	376500	383000	6500	110960	47558	130	13	6	0
401	West	383500	391000	7500	110980	47560	151	16	8	1
401	West	392000	402500	10500	111000	47570	210	21	10	1
401	West	403000	412500	9500	111020	47580	190	19	9	1
401	West	413000	421500	8500	111040	47594	170	17	8	1
401	West	422000	424500	2500	111060	47600	50	5	2	1
401	West	425000	429000	4000	111080	47603	80	8	4	1
401	West	428500	434000	5500	111100	47607	110	11	5	1
401	West	434500	441500	7000	111120	47612	140	14	7	1
401	West	442000	443500	1500	111140	47625	30	3	1	0
401	West	449500	458000	8500	111180	47631	170	17	3	0
401	West	458500	462500	4000	111200	47643	80	8	3	0
401	West	463000	468000	5000	111220	47652	100	10	5	1
401	West	468500	472000	3500	111240	47660	70	7	1	0
401	West	472500	474000	1500	111260	47665	30	3	2	0
401	West	474500	476500	2000	111280	47667	40	4	2	0
401	West	476500	482500	6000	111300	47672	120	12	5	0
401	West	483000	486500	3500	111320	47675	70	7	3	0
401	West	487000	495000	8000	111340	47680	160	16	4	1
401	West	495500	497500	2000	111360	47688	40	4	2	0
401	West	498000	507000	9000	111380	47689	180	18	9	1
401	West	507500	519500	12000	111400	47700	240	24	11	1
Total				**172,500**			**3,451**	**346**	**152**	**15**

The distribution of rut depth is used to compare the section lengths of the respective road segments. The frequency, distribution plot and distribution parameters are listed and compared for all 27 road segments. Figure 4.3 illustrates the rut depth distributions for two road segments by using different section lengths. The histogram of the rut distribution is on the left-hand plots and the same distribution, in cumulative format, is depicted on the right. Table 4.2 shows the comparison of distribution parameters of rut depth of a road segment (Highway 401 Eastbound ID 111370) with different section lengths. Table 4.3 summarizes the distribution parameters of rut depth of all 27 road segments for four types of road section lengths. This table illustrates the variability of field-evaluated rut depth due to changes in section length. This can be misleading when road sections are presented through long treatment lengths and if the maintenance decision is made based on this. The effect of this variability is further discussed in section 4.5.

Table 4. 2: Comparison of Distribution Parameters of Rut Depth of a Road Segment (Highway 401 Eastbound ID 111370) with different Section Lengths

Distribution Parameters	**Section Length**			
	50m	**500m**	**1,000m**	**10,000m**
Sample Size	170	17	8	1
Mean Rut Depth (mm)	3.08	3.09	2.92	1.05
Standard Deviation (mm)	1.44	1.15	0.84	N/A[2]
Variance	2.07	1.32	0.71	N/A
C.O.V	0.48	0.37	0.29	N/A
95^{th} Percentile	5.45	4.98	4.30	N/A
75^{th} Percentile	4.05	3.86	3.49	N/A
50^{th} Percentile	3.08	3.09	2.90	N/A

4.4.2 Investigation of Overall Condition of Pavement

In this study, the IRI, mean value of the old PCI (refer to equation 4.1 from the manual survey) and the new PCI value (refer to equation 4.2 from automated detection and calculation) are compared to better understand the difference in the overall condition. In this comparison, the given section lengths are extracted from the data of the selected road segments. Figure 4.4 illustrates the difference in mean IRI and the mean PCI value of all road segments for the four types of section lengths. In Figure 4.4, it is observed that the manual surveys estimate higher defects over the shorter sections (50m and 500m), thus giving a lower PCI compared to the longest section (10,000m). The effect of this is further discussed in section 4.5.

[2] N/A= Not Applicable; distribution parameters are not available as only one sample is available for 10,000m section in this road segment.

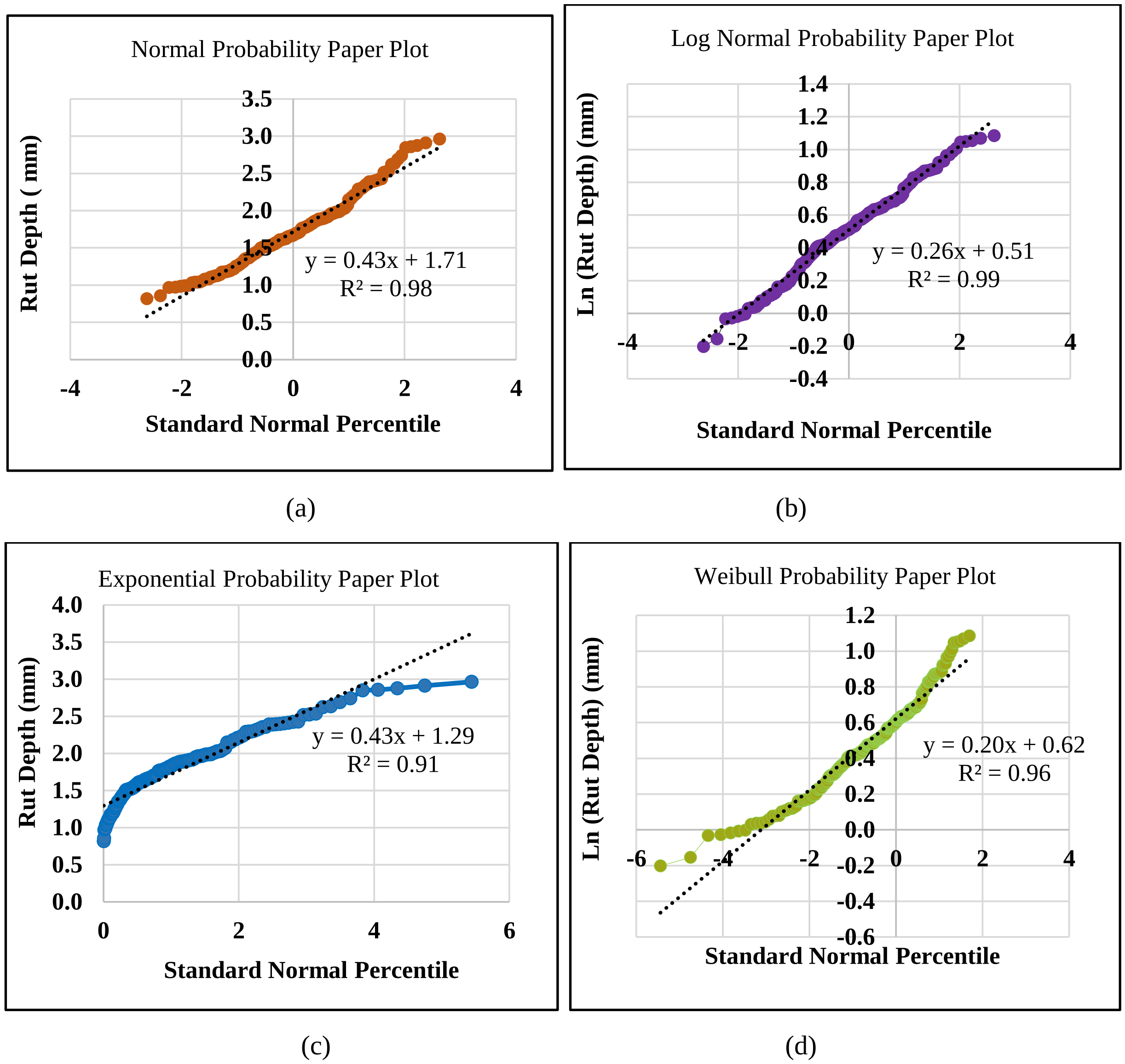


Figure 4.2: Probability plot of rut depth of selected road section: (a) normal probability plot; (b) log-normal probability plot; (c) exponential probability plot; (d) weibull probability plot.

Table 4.3: Summary of Distribution Parameters of Rut Depth of all Road Segments

Highway	Direction	Distribution Parameters of Rut Depth											
		50m Section			500m Section			1,000m Section			10,000m Section		
		Sample Size	Mean Rut Depth (mm)	St. Dev.[3] (mm)	Sample Size	Mean Rut Depth (mm)	St. Dev. (mm)	Sample Size	Mean Rut Depth, (mm)	St. Dev. (mm)	Sample Size	Mean Rut Depth (mm)	St. Dev. (mm)
401	East	230	1.714	0.429	23	1.717	0.353	11	1.717	0.319	1	1.901	N/A[4]
401	East	170	3.083	1.439	17	3.089	1.148	8	2.92	0.841	1	1.046	N/A
401	East	121	2.804	0.484	12	2.805	0.381	6	2.805	0.328	0	N/A	N/A
401	East	140	2.963	0.735	14	2.968	0.601	7	2.967	0.328	0	N/A	N/A
401	East	229	3.111	0.712	23	3.108	0.552	10	3.005	0.432	1	3.024	N/A
401	West	130	3.92	1.302	13	3.915	1.101	6	3.895	1.062	0	N/A	N/A
401	West	151	2.906	0.828	16	2.968	0.519	8	2.871	0.197	1	2.794	N/A
401	West	210	3.769	0.547	21	3.772	0.358	10	3.773	0.356	1	3.805	N/A
401	West	190	4.057	0.992	19	4.046	0.762	9	4.08	0.756	1	4.009	N/A
401	West	170	3.233	1.324	17	3.241	1.06	8	3.286	0.915	1	3.347	N/A
401	West	50	4.285	2.315	5	4.285	2.127	2	3.811	2.609	1	3.872	N/A
401	West	80	3.244	1.039	8	2.968	0.519	4	3.252	0.885	1	3.3	N/A
401	West	110	2.677	0.535	11	2.679	0.473	5	2.792	0.279	1	2.722	N/A
401	West	140	2.452	0.957	14	2.439	0.86	7	2.438	0.757	1	2.546	N/A
401	West	30	1.783	0.341	3	1.782	0.273	1	1.934	N/A	0	N/A	N/A
401	West	170	0.481	0.989	17	0.582	1.093	3	2.456	0.393	0	N/A	N/A
401	West	80	1.155	1.304	8	1.215	1.336	3	2.553	0.552	0	N/A	N/A
401	West	100	4.585	1.379	10	4.597	1.323	5	4.596	1.285	1	4.403	N/A
401	West	70	0.172	0.596	7	0.291	0.771	1	2.396	N/A	0	N/A	N/A
401	West	30	4.956	1.135	3	4.957	0.498	2	4.234	1.4	0	N/A	N/A
401	West	40	3.628	0.889	4	3.646	0.684	2	4.067	1.013	0	N/A	N/A
401	West	120	4.973	2.111	12	4.987	1.639	5	5.297	1.303	0	N/A	N/A
401	West	70	1.96	1.035	7	2.142	0.392	3	2.194	0.381	0	N/A	N/A
401	West	160	1.304	1.396	16	1.378	1.43	4	2.741	0.137	1	2.916	N/A
401	West	40	4.262	0.883	4	4.267	0.561	2	4.089	0.291	0	N/A	N/A
401	West	180	3.6	1.004	18	3.594	0.637	9	3.597	0.575	1	3.403	N/A
401	West	240	1.579	0.311	24	1.577	0.17	11	1.578	0.133	1	1.574	N/A
Total		**3,451**			**346**			**152**			**15**		

[3] St. Dev.=Standard Deviation;
[4] N/A= not available; as 10,000m section is not available in this road segment.

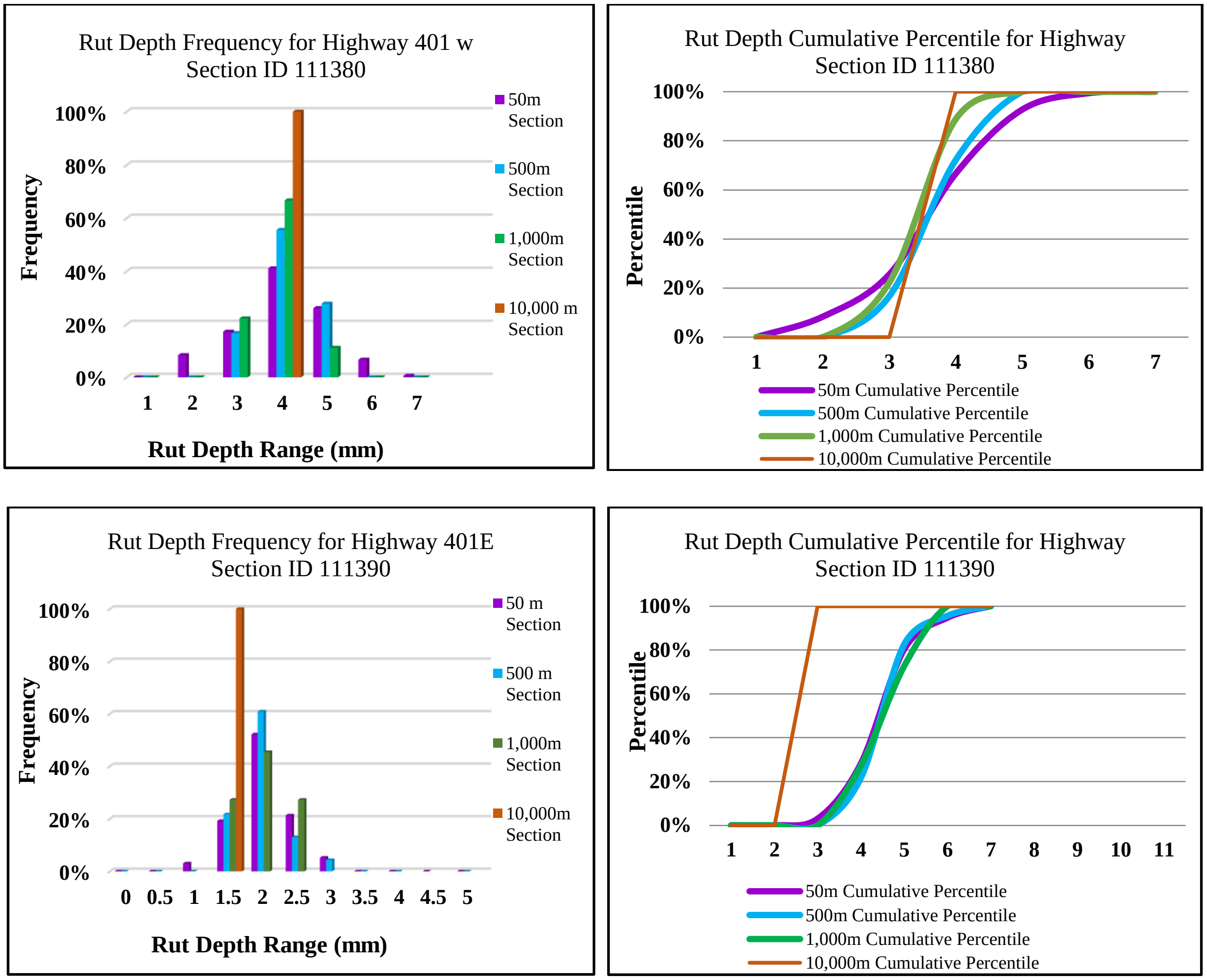


Figure 4.3: Comparison of rut distribution between road segments using different section lengths.

The difference in the overall road segment conditions for each section length is further investigated by comparing the rut depth, IRI and PCI over a continuous road segment. Figure 4.5 illustrates the variability comparison of rut depth, IRI and PCI over the continuous 11,500m road segment (from 507,000m to 518,500m) of Highway 401 Eastbound (Section ID 111390). This figure validates that short sections (50m section) show higher rut depth over a continuous road segment than all other sections. A similar pattern is found for IRI values within short sections.

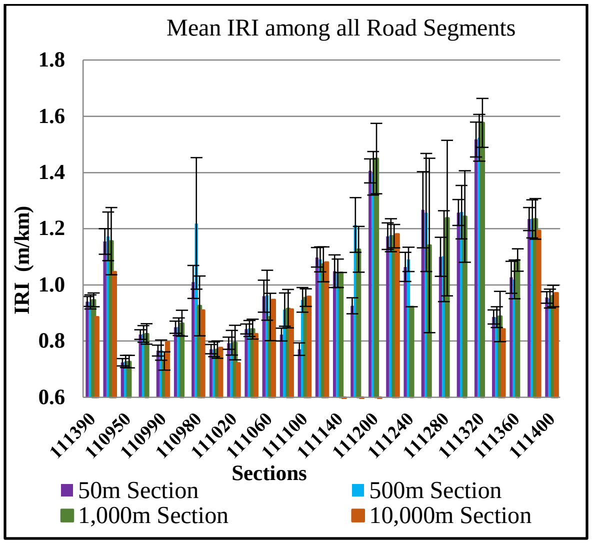
As discussed in the previous section, the Ontario highway system is moving to an automated survey regime from a manual rating system. In this study, the mean value of the previous PCI value (refer to equation 4.1 from the manual survey) and the new PCI value (refer to equation 4.2 from automated detection and calculated) are compared. In this comparison, the given section lengths are extracted from the data of the selected road segments. Figure 4.6 illustrates the difference in the old PCI value to the new automated system. Table 4.4 shows the variability in PCI value for both the manual and automated surveys due to the change in section length.

Table 4.4: Variability in PCI Value in both Manual and Automated Survey due to Change in Section Length

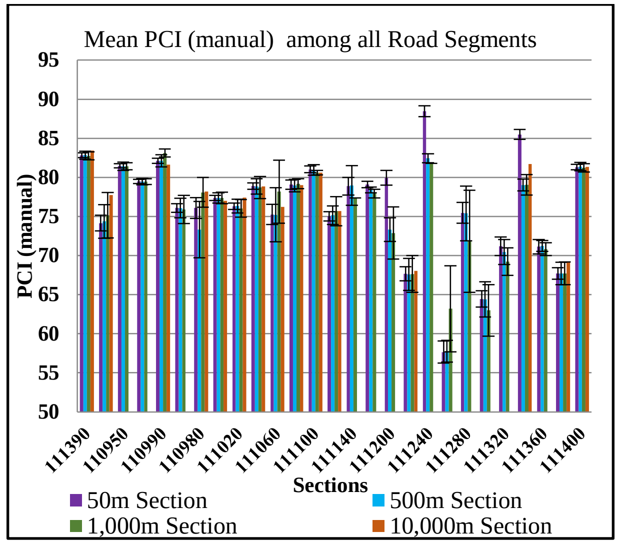
Change in PCI Value	**Old PCI Vs New PCI** 50m Section	**500m Section**	**1000m Section**	**10000m Section**
Average(New-Old)/Old	9.6%	10.7%	-1.3%	-1.1%
Section with New PCI <Old PCI	7%	0%	70%	67%
Section with New PCI >Old PCI	93%	100%	30%	33%

4.4.3 Investigating the Influence of Section Length on Maintenance Decisions

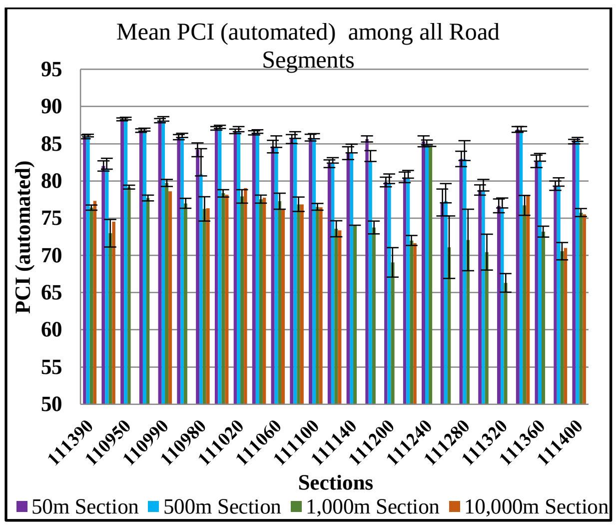
Since the rut distribution shows variation on the same road segment with changing section lengths, this will impact maintenance decisions. For this reason, a Monte Carlo simulation is carried out with different section lengths to estimate the probability of work being triggered. Three section lengths are investigated in this simulation: 50m, 500m, and 1000m. This simulation is carried out for 10,000 samples and considers rut depth as a random variable. The maintenance requirement is triggered when PCI deteriorates to a level below 80. Most of the road segments in this simulation are selected from Ontario’s major freeways, namely Highway 401 Eastbound and Westbound. The maintenance trigger value is selected as 80 because they are maintained regularly and their average PCI value is above 80. Based on the analyses of the road section distributions, the conditions can be modelled by using either a normal or a log-normal distribution. For simplicity, a normal distribution is used for this exercise. The distribution properties and results of the Monte Carlo simulation are depicted in Table 4.5.



(a)

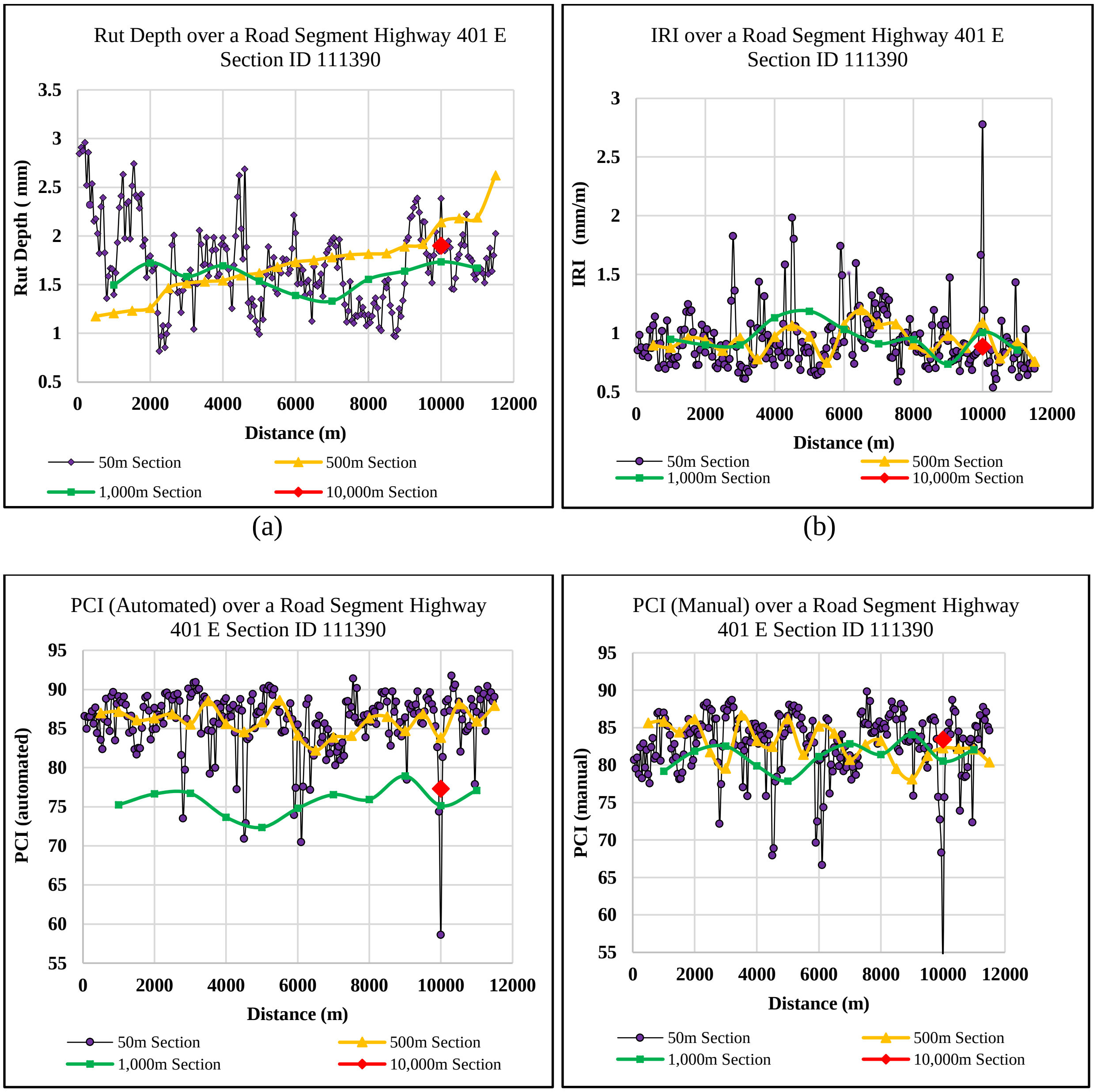


(b)



(c)

Figure 4.4: Comparison of (a) mean IRI, (b) mean PCI (manual surveys), and (c) mean PCI (automated surveys) of all road segments for all section lengths.



(a) (b)

(c) (d)

Figure 4.5: Comparison of (a) rut depth (b) IRI, (c) PCI (automated), and (d) PCI (manual) over a road segment of highway 401 E (from 507,000m to 518,500m).

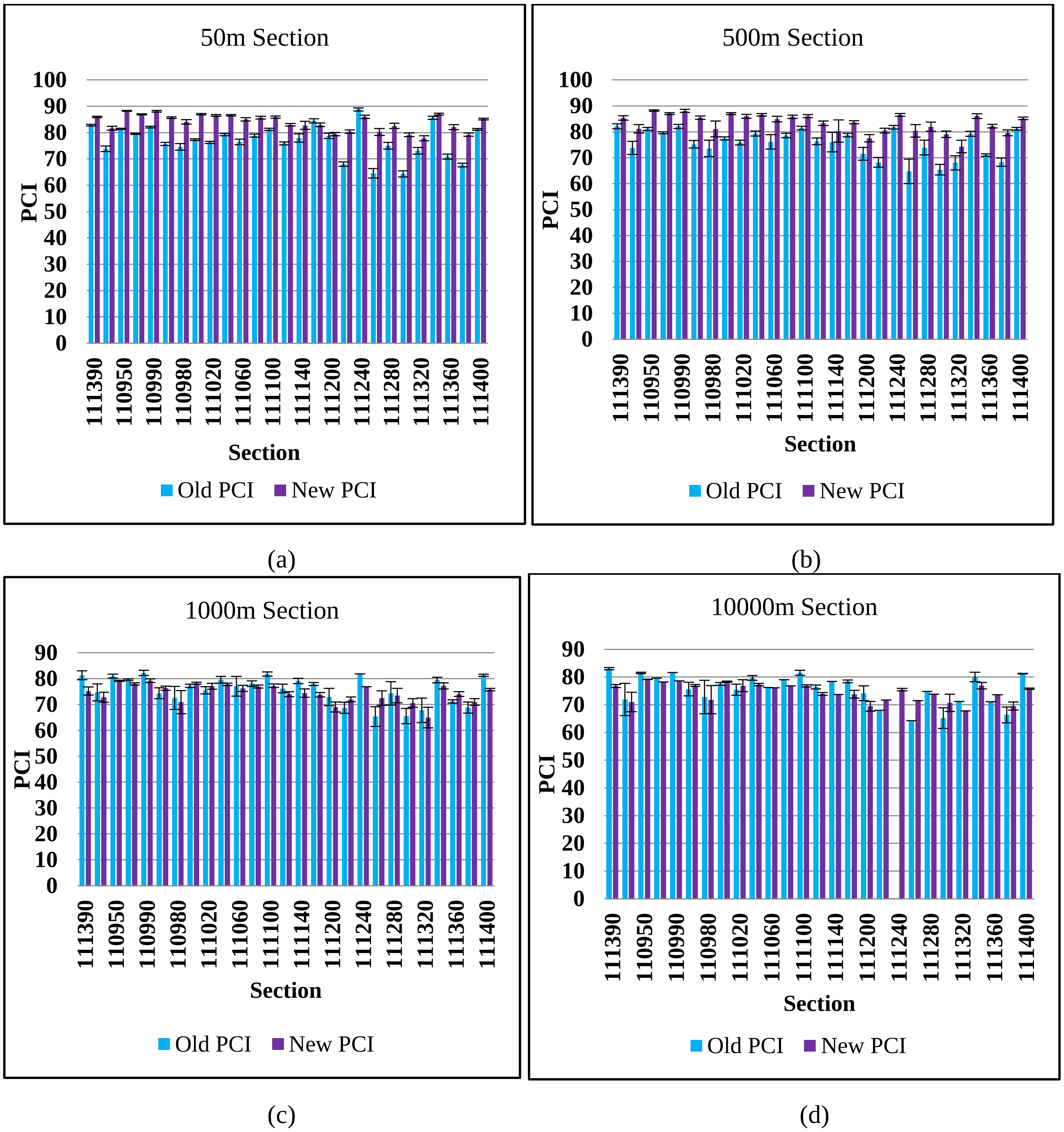


Figure 4.6: Comparison of mean PCI for (a) 50 m Section, (b) 500 m Section, (c) 1,000 m Section, and (d) 10,000 m Section

Table 4.5: Summary of Distribution Properties and Results of the Monte Carlo Simulation

Distribution Properties Used in the Monte Carlo Simulation						
Condition Item	**50m Section**		**500m Section**		**1000m Section**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Rut Scaled	94.29	1.43	94.28	0.68	94.27	0.319
IRI Scaled	81.18	5.5	82.6	2.62	81.08	1.619
DMI	98.35	2.25	92	3.65	98.34	1.260
New PCI	85.92	1.09	85.64	1.98	85.844	0.339

Results of the Monte Carlo Simulation			
Maintenance Decision	**50m Section**	**500m Section**	**1000m Section**
Probability of Maintenance Being Triggered	0.064	0.0021	0.00012
No. of Sections Most Likely to be Triggered	640	21	1.2
Equivalent Length Needing Maintenance	32km	10.5km	1.2km

4.5 Discussion on Results

In comparing the rut depth distributions among different section lengths, it is observed that the evaluations of road conditions vary depending on the section length. Rut distribution of the first road segment (Section ID 111380) in Figure 4.3 illustrates that 10,000m section lengths evaluate roads with low rut depth of approximately 4mm, whereas 1,000m section lengths evaluate roads with rut depth between 3mm and 5mm. In this road segment, the shorter section (50m section) length is able to identify higher rut depth levels as high as 7mm. In the second segment (Section ID 111390), longer section lengths (10,000m) suggest an overall rut depth of approximately 1.5mm and over. Similarly, the 1,000m section length shows rut depth between 1.5mm to 2.5mm. The short section (50m) suggests a higher rut depth of approximately 3.5mm.

However, the distribution does not determine whether higher rut sections are equally distributed over the entire section length or if they are occurring in only part of the section. For this reason, a strip map plot per running meter or kilometer is required for pavement evaluation. By comparing the rut depth of these two road segments shows an entirely different picture of these section lengths. The first road segment would not be of concern if data from the longer section (10,000m) was considered with a rut depth of 4mm. However, the distribution of shorter sections focuses on some isolated sections that would be above or near 7mm deep. Likewise, the second segment would not be of concern if the average rut depth of the longer section (10,000m) is considered. The point observed here can be further emphasized by considering the reported statistics as presented in Table 4.2. This table shows how misleading the statistical information can be when road sections are presented through long treatment lengths. It is found that the midpoint (both the average and 50th percentile) varies significantly among different section lengths. The 75th percentile seems to be a more stable statistical parameter when compared to the midpoint. The standard deviation also differs significantly for this given section length. Similar scenarios are observed for the other 26 segments.

To investigate the impact of section lengths on the overall pavement condition, PCI and IRI are compared. Since PCI is a deduced value, higher values indicate better conditions. For IRI, lower values indicate better conditions. From Figure 4.4, it is observed that longer sections (10,000m) present lower IRI values for most of the road segments. It is found that IRI of the 50m section is not very different from the 500m and 1,000m sections. This might occur due to the precise reading from the automated device or profile used for roughness measurement over the entire section length. It is also observed that the manual surveys estimate a higher extent of defects over the shorter sections (50m and 500m). Thus, this could result in lower PCI as compared to those obtained for longer sections (10,000m). The PCI value from the automated survey suggests that with shorter section lengths, total distresses measured by the automated survey are less compared to longer sections. The PCI from the automated survey is noticeably lower on the longer sections with more defects compared to the shorter section lengths. This might occur since the new PCI is calculated from the distresses identified by automated detection, which show slightly more faults.

As one would expect from the variation of rut distribution for different section lengths, the length of a section might also impact how much work would be triggered. Assuming a common intervention level for 50m, 500m, and 1000m sections, maintenance requirements are compared. From the Monte Carlo simulation, it is found that 50m sections show a higher probability of maintenance requirements (probability 0.064) than (probability 0.0021) in 500m sections. An equivalent of 640 sections require maintenance, whereas only 21 sections require maintenance if the section length is 500m. 1000m sections show the lowest probability of maintenance requirements (probability 0.00012). It reveals that longer sections overlook some parts of the roads that require maintenance and can potentially result in accelerated deterioration. The Monte Carlo simulation effectively demonstrates the impact of different treatment lengths in the decision-making process. Although the selection of an appropriate section length is mainly related to practical aspects, this analysis shows that effective maintenance management requires that these sections not be too long.

4.6 Chapter Summary

This chapter investigates the impact of road section lengths on overall pavement performance evaluation. The impact on maintenance decisions due to section lengths selected for performance evaluation is also investigated.

Experimental investigations include analyses of rut depth distribution and comparison of performance evaluated by PCI and IRI for different section lengths. Since rut distribution and PCI are varied due to changes in length of road sections, maintenance decisions are also analysed by using the Monte Carlo simulation.

Based on the comparison of rut depth distribution among different section lengths, it is found that the evaluation of road conditions varies depending on the section length. It is noted that most of the longer sections (10,000m) evaluate the road with low rut depth and the shorter sections detect higher rut depth. The short sections also indicate that the rut depth is relatively evenly distributed comparing to the longer sections. It is also found that the midpoint (both the average and 50th percentile) varies significantly among different section lengths. The standard deviation also differs significantly depending on the section length. Longer sections might overlook some parts of severely damaged roads in need of maintenance due to the average value of rut depth over a long section.

To avoid acceleration of further deterioration of these parts, it is efficient to compare the shorter sections to the longer sections. There are a number of long sections in Ontario highway systems that skew the outcome of the performance measures and may cause difficulties in both treatment selection and pavement condition reporting. Thus, performance reported from sections lengths that are too long are misleading when compared to the true performance of the network.

Comparison of PCI shows that the old PCI estimate has a higher extent of defects over the shorter sections (50m and 500m) and results in a lower PCI value. On the other hand, over the longer sections, lower PCI values are obtained with automated surveys values when compared to the shorter section lengths.

Based on the Monte Carlo simulation, it is found that 50m sections show a higher probability for maintenance requirements than 500m sections. As a result, maintenance decisions for shorter treatment lengths trigger more work. When short lengths are used it may also become difficult to effectively manage the network level.

This chapter emphasizes the value of understanding the full distribution of defects for road lengths, rather than considering a single statistical parameter. However, communicating full distribution outputs can be complex and difficult to understand. For this reason, it is important to use consistent road section lengths when reporting pavement conditions and condition trends over time.

In addition, section lengths also significantly influence the processes to analyse the required works programme. One of two recommended analytical processes outlined below may be used:

1. Undertake dynamic segmentation prior to the PMS analyses and verify the applicability of these section lengths in the field. These section lengths need to be reviewed on an annual basis as road condition may change significantly from one year to another; or,
2. Analyse fixed section length in the PMS system. For this, a section length of 500m is recommended for Ontario highways. Following the analysis, the recommended works programme is determined by rationalising the recommended treatment in order to yield

practical treatment lengths and/or to combine sections into one length of similar timing and types or treatments are recommended for adjacent sections.

Based on this analysis, the section length for specific KPIs can be selected. The next chapter focuses on analysis of KPI models through regression. The individual KPI values are compared against independent variables that impact pavement performance.

CHAPTER 5
ANALYSIS OF EXISTING ESTIMATES OF THE PERFORMANCE INDEX

Generally, the prediction models of KPIs are estimated by using the OLS approach. However, OLS may be inefficient if unobserved factors influencing individual KPIs are correlated with each other. This chapter proposes the use of an approach called the SUR method instead.

The work of this chapter was presented at the Transportation Research Board (TRB) meeting in January 2017 (Jannat 2017). Part of this chapter was also presented at the Transportation Association of Canada (TAC) Conference (Jannat 2015).

5.1 Introduction

The results of any PMS analysis and maintenance recommendations are dependent on selected KPIs. That being said, KPI models are to be developed by analyzing the significance of specific variables that affect pavement performance. Developing a comprehensive and accurate KPI model to predict overall pavement conditions from specific distresses and cracking continues to be a challenge in pavement engineering (Haas 1994). Generally, KPI models are regression models of various pavement performance -related variables. The OLS-based regression is the common practice in this case.

For Ontario highway systems, several KPIs have been used over the past 30 years. In Ontario, PCI and DMI models are developed by using the OLS approach based on the rating of a selected 15 categories of distresses classified by the MTO (MTO 2007).

In Ontario, PCI, DMI, RCI and IRI are used as dependent variables in KPI models to predict pavement performance. These models are estimated by using the OLS approach from the selected distress categories classified by the MTO. However, pavement deterioration may be affected by many factors. These unobserved factors influencing pavement performance may be correlated or not. OLS may result in biased estimates if the unobserved factors influencing different KPIs are correlated. If they are highly correlated, there is a chance that the OLS may not be able to retrieve efficient parameter estimates for the KPI regression models. As a result, an alternative regression estimation approach is required because it can consider any correlation among unobserved factors within the KPI models, while estimating the KPI regression coefficients (Zellner 2006, and Greene 2003). In this regard, the SUR has the potential and may prove to be a better modeling approach for KPI regressions.

5.2 Pavement Performance Data

The 15 distress categories classified by the MTO for flexible pavement are listed in Table 5.1. These distresses are rated in a subjective manner. For each distress, severity and extent are rated by five categories shown in Table 5.2 (Chong 1989). The average subjective rating is the only data available in the MTO PMS-2 database. The multiple raters' ratings are not available to analyze the subjective variability. The road sections also contain all information of the respective M&R undertaken during the service life (Kazmierowski 2001).

Table 5.1: Specific Distress Categories of Ontario's Flexible Pavement (for Manual Survey)

Distress of Flexible Pavement
1. Ravelling and Coarse Aggregate Loss
2. Flushing
3. Rippling and Shoving
4. Wheel Track Rutting
5. Distortion
6. Longitudinal Wheel Track: Single and Multiple
7. Longitudinal Wheel Track: Alligator
8. Centreline: Single and Multiple Cracking
9. Centreline: Alligator Cracking
10. Pavement Edge: Single and Multiple Cracking
11. Pavement Edge: Alligator Cracking
12. Transverse: Half, Full and Multiple Cracking
13. Transverse: Alligator Cracking
14. Longitudinal Meandering and Mid-lane Cracking
15. Random Cracking

From the MTO-PMS-2 database, a total of 61 road segments from Ontario's major highway networks are selected. The database includes all historical performance information, including condition survey information. From these road segments, 158 pavement treatment cycles are selected. These performance cycle lengths vary from two to 15 years.

Table 5.2: Condition Rating of Extent and Severity of Distress

Density/Extent	Condition Rating
Few: less than 10% of pavement surface affected	1
Intermittent: 10-20% of pavement surface affected	2
Frequent: 20-50% of pavement surface affected	3
Extensive: 50-80% of pavement surface affected	4
Throughout: 80-100% of pavement surface affected	5
Severity	
Very Slight	1
Slight	2
Moderate	3
Severe	4
Very Severe	5

5.3 Joint Estimate Method of KPI Models

5.3.1 OLS Approach

As discussed in the previous section, PCI is used for M&R decision trees as an overall pavement condition index in many PMS. The PCI is composed of two sub-indices, respectively representing IRI and DMI. In Ontario, the formula used to calculate PCI is defined as follows (MTO 2007):

For Asphalt concrete (AC) Pavement,

$$PCI = Max(0,Min(100,13.75 + 9 \times DMI - 7.5 \times IRI)) \tag{5.1}$$

For Composite Pavement,

$$PCI = Max(0,Min(100,13.75 + 8.5 \times DMI - 11 \times IRI)) \tag{5.2}$$

The formula used to calculate DMI is as shown in the following:

For AC Pavement,

$$DMI = 10 * (208 - \sum_{k}^{N} (S_k + D_k) \times W_k) / 208 \tag{5.3}$$

For Composite Pavement,

$$DMI = 10 * (196 - \sum_{k}^{N} (S_k + D_k) \times W_k) / 196 \tag{5.4}$$

Where,

N is the Number of Distresses Related to a Given Pavement Type
S_k is the Severity Rate of Distress *k*
D_k is the Density Rate of Distress *k*
W_k is the Weighting Factor of Distress *k*

Since RCI is also a function of IRI, the PCI formula is also being expressed as:

For AC Pavement,

$$PCI = Max(0, Min(100, 13.75 + 9 \times DMI - 7.5 \times e^{(8.5 - RCI)/3.02})) \tag{5.5}$$

For Composite Pavement,

$$PCI = Max(0, Min(100, 20.5 + 8.5 \times DMI - 11 \times e^{(8.49 - RCI)/2.44})) \tag{5.6}$$

The formula used to calculate RCI is shown below:

For AC Pavement,

$$RCI = Max(0, Min(10, 8.5 - 3.02 \times ln(IRI))) \tag{5.7}$$

For Composite Pavement,

$$RCI = Max\ (0, Min\ (10, 8.49 - 2.44x1n(IRI))) \tag{5.8}$$

The OLS approach is used for estimating parameters of these KPI models. For OLS, standard multivariate regression requires that each of the 'p' dependent variables has exactly the same design matrix as per below: (Beasley 2008; Montgomery 2009):

$$y_{N\times p} = \beta_{k\times p}\, x_{N\times k} + \varepsilon_{N\times p} \tag{5.9}$$

Where,
y is a matrix of *p* dependent variables,
β is a matrix of coefficients,
x is a *k*-dimensional design matrix, and
ε is an error matrix, which is assumed to be distributed as N (Nxp) ($0, \Sigma \otimes IN$)

Multivariate regression theory using OLS assumes that all of the coefficients in the model are unknown and to be estimated from the data as (Beasley 2008; Montgomery 2009):

$$\hat{\beta} = (x'x)^{-1}\ (x'y) \tag{5.10}$$

Where,
x' is transpose matrix of x
$(x'x)^{-1}$ is inverse matrix of $(x'x)$

5.3.2 Application of Generalized Least Squares (GLS) Approach through 'SUR' Model

This 'SUR' approach is used with the application of the GLS approach. This method is a generalization of multivariate regression which applies a vectorized parameter model. The *'y'* matrix is vectorized by vertical concatenation, yv. The design matrix, D, is formed as a block diagonal with the j^{th} design matrix, x_j, on the j^{th} diagonal block of the matrix. The model is expressed as (Beasley 2008):

$$E[y_{(NXp)}] = \{x_{1\,(NXm1)}\,\beta_{1\,(m1X1)}, x_{2\,(NXm2)}\,\beta_{1\,(m2X1)}, x_{j\,(NXmj)}\,\beta_{1\,(mjX1)}, x_{p\,(NXmp)}\,\beta_{1\,(mpX1)}\} \qquad (5.11)$$

Where,
m_j is the number of parameters estimated (columns) by the j^{th} design matrix, x_j..
To illustrate in matrix notation, the SUR model is expressed as (*22*):

$$\begin{array}{ccccc} & \boldsymbol{E(y_v)} & & \mathbf{D} & \mathbf{B} \\ \boldsymbol{E(y_v)} = & \begin{bmatrix} \hat{\boldsymbol{y}}_1 \\ \hat{\boldsymbol{y}}_2 \\ \cdots \\ \hat{\boldsymbol{y}}_j \\ \cdots \\ \hat{\boldsymbol{y}}_p \end{bmatrix} \begin{matrix} (NX1) \\ (NX1) \\ \cdots\cdots \\ (NX1) \\ (NX1) \end{matrix} & = & \begin{bmatrix} \boldsymbol{x_1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ (NX\,m_1) & \boldsymbol{x_2} & \mathbf{0} & \mathbf{0} \\ & & & \mathbf{0} \\ & (NX\,m_2) & \mathbf{0} & \mathbf{0} \\ & (sym) & \boldsymbol{x_j} & \boldsymbol{x_p} \\ & & (NX\,m_j) & (NX\,m_j) \end{bmatrix} & \begin{bmatrix} \boldsymbol{\beta_1}\ _{(m1X1)} \\ \boldsymbol{\beta}\ _{\boldsymbol{2}\ (m2X1)} \\ \cdots \\ \boldsymbol{\beta}\ _{\boldsymbol{j}\ (mjX1)} \\ \cdots \\ \boldsymbol{\beta}\ _{\boldsymbol{p}\ (mpX1)} \end{bmatrix} \\ & (Np\,X1) & & (Np\,XM) & (M\,X1) \end{array} \qquad (5.12)$$

Where,
M is the total number of parameters estimated over the p models, $M = \sum_{j=1}^{p} m_j$

To solve for the parameter estimates:

$$\underset{}{\hat{B}} = [\underset{[M\,X\,N_p]}{D'}\quad \underset{[N_p\,X\,N_p]}{Q^{-1}}\quad \underset{[N_p\,X\,M]}{D}]^{-1}\quad [\underset{[M\,X\,N_p]}{D'}\quad \underset{[N_p\,X\,N_p]}{Q^{-1}}\quad \underset{[N_p\,x1]}{y_v}] \qquad (5.13)$$

Where,
Q is a weight matrix based on the residual covariance matrix of the y variables and is formed as:

$$\underset{[N_p\text{ x }N_p]}{Q} = \underset{[\text{p x }p]}{\widehat{\Sigma \otimes I_N}}$$

With this approach, parameters of performance variables are estimated for the selected KPI model. In this study, the severity and extent of all distresses (listed in Table 5.1) are considered as independent variables in estimating KPI models. For some road sections, the rating of distresses is found as '0', these values are scaled up to '1' and all the ratings are scaled up accordingly. In addition to these specific 15 distresses, the length of pavement performance cycles (life span between two subsequent treatment), AADT, percentage of trucks, resilient modulus of subgrade soil and rut depth in mm (measured by an automated device) are also considered as independent variables.

Pavement performance cycle lengths significantly affects performance and deterioration distress patterns. Pavement performance deteriorates over time and the rate of deterioration increases over time. Therefore, pavement under the same traffic loads and other conditions with higher cycle lengths will not perform like shorter cycle lengths. Moreover, the propagation of cracking will have a different pattern and acceleration rate. For this reason, performance cycle length is considered to be a variable in the performance models. Likewise, traffic loads such as AADT and the percentage of trucks are important variables that contribute to pavement damage, having a substantial effect on major distresses on Ontario highways (Jannat 2015). Similarly, strength (resilient modulus) of subgrade soil has a significant effect on pavement distresses, especially for causing rut depth (Jannat 2015). Moreover, absolute rut depth in mm, which is recently measured by an automated device, is more precise than the manual rating of wheel track rutting (distress 4 in Table 5.1). For this reason, absolute rut depth in mm is considered as a variable for PCI and IRI models. Severity and extent of shoulder cracking are also considered as variables in these models.

Finally, the pavement performance cycle, AADT, percentage of trucks, strength of subgrade soil and the severity and extent of shoulder cracking, in addition to the 15 distresses categorized by the MTO, are considered as independent variables for estimating the models of DMI, RCI, PCI and IRI. Rut depth is taken as an additional independent variable for PCI and IRI models only.

After selecting the independent variables of the models, a logarithmic transformation is applied in both dependent and independent variables. Logarithmic transformation is considered so that ‘elasticity' or ‘marginal effect or sensitivity’ can be estimated directly from the models. Elasticity is defined as the unit change in the *y* variable for a unit change in the *x* variable. It can also be defined as how the dependent variable changes when the independent variable changes by an additional unit, holding all other variables in the equation constant (i.e. partial derivative). The following KPI models (taking log-log in both sides) are considered for analysis:

$$DMI = e^{\beta_0} e^{\beta_1 \ln(x_1)} e^{\beta_2 ln(x_2)} \dots \dots \dots \dots \dots \dots \dots \dots e^{\beta_{36} ln(x_{36})} \tag{5.14}$$

Or, $DMI = e^{\beta_0} x_1^{\beta_1} \ x_2^{\beta_2} \ \dots \dots \dots \dots \dots \dots \dots \dots x_{36}^{\beta_{36}}$

$$\text{RCI}= e^{\beta_0} x_1^{\beta_1} \ x_2^{\beta_2} \ \dots \dots \dots \dots \dots \dots \dots \dots x_{36}^{\beta_{36}} \tag{5.15}$$

$$PCI = e^{\beta_0} x_1^{\beta_1} \ x_2^{\beta_2} \ \dots \dots \dots \dots \dots \dots \dots \dots x_{37}^{\beta_{37}} \tag{5.16}$$

$$IRI = e^{\beta_0} x_1^{\beta_1} \ x_2^{\beta_2} \ \dots \dots \dots \dots \dots \dots \dots \dots x_{37}^{\beta_{37}} \tag{5.17}$$

Where,

β_0, β_1, …….. β_{37} are Regression Coefficients

x is the Independent Variable

x_1 is Severity of Ravelling and Coarse Aggregate Loss
x_2 is Extent of Ravelling and Coarse Aggregate Loss
x_3 is Severity of Flushing
x_4 is Extent of Flushing
x_5 is Severity of Rippling and Shoving
x_6 is Extent of Rippling and Shoving
x_7 is Severity of Wheel Track Rutting
x_8 is Extent of Wheel Track Rutting
x_9 is Severity of Distortion
x_{10} is Extent of Distortion
x_{11} is Severity of Longitudinal Wheel Track Cracking (Single and Multiple)
x_{12} is Extent of Longitudinal Wheel Track Cracking (Single and Multiple)
x_{13} is Severity of Longitudinal Wheel Track Alligator Cracking
x_{14} is Extent of Longitudinal Wheel Track Alligator Cracking
x_{15} is Severity of Centreline Cracking (Single and Multiple)
x_{16} is Extent of Centreline Cracking (Single and Multiple)
x_{17} is Severity of Centreline Alligator Cracking
x_{18} is Extent of Centreline Alligator Cracking
x_{19} is Severity of Pavement Edge Cracking (Single and Multiple)
x_{20} is Extent of Pavement Edge Cracking (Single and Multiple)
x_{21} is Severity of Pavement Edge Alligator Cracking
x_{22} is Extent of Pavement Edge Alligator Cracking
x_{23} is Severity of Transverse Cracking (Half, Full and Multiple)
x_{24} is Extent of Transverse Cracking (Half, Full and Multiple)
x_{25} is Severity of Transverse Alligator Cracking
x_{26} is Extent of Transverse Alligator Cracking
x_{27} is Severity of Longitudinal Meandering and Mid-lane Cracking
x_{28} is Extent of Longitudinal Meandering and Mid-lane Cracking
x_{29} is Severity of Random Cracking
x_{30} is Extent of Random Cracking
x_{31} is Severity of Shoulder Cracking
x_{32} is Extent of Shoulder Cracking
x_{33} is Pavement Cycle Length Between Treatments
x_{34} is AADT
x_{35} is Percentage of Trucks
x_{36} is Strength of Subgrade Soil in *Mpa*
x_{37} is Rut Depth in mm

5.5 Results of Joint Estimate of KPI Models

In this study, the SUR approach is used to estimate all parameters of KPI models simultaneously, whilst the correlations among all variables are considered. Four equations (equation 5.14, 5.15, 5.16 and 5.17) are developed to simultaneously predict the pavement condition based on the extent and severity of distresses and other variables. Statistical analyses are carried out by using the software "SAS" for the SUR method.

The fitting quality of the single equation is evaluated by the coefficients of determination of estimation (R^2), standard errors of the estimate (SEE) and by the standard errors (SE) of the estimated parameters. The significance of each multiple equation are verified by the F value. F_{obs} of the model is compared to $\mathbf{F_{critical}}$. The model is considered as significant if $\mathbf{F_{obs}}$ is greater than $\mathbf{F_{critical}}$. $\mathbf{F_{critical\ for}}$ α =0.025 (for 97.5% confidence interval), p-1=35 (for DMI and RCI) or 36 (for PCI and IRI); n-p=122 (for DMI and RCI) ,123 (for PCI AND IRI) =1.48 .

Analysis of Variance (ANOVA) calculations of jointly estimated KPI models are shown in Table 5.3. From Table 5.3, $\mathbf{F_{obs}}$ value of DMI, RCI, PCI and IRI models are found as 20.87, 3.32, 18.15 and 2.56, respectively. Therefore, all these models are found to be significant since $\mathbf{F_{obs}} > \mathbf{F_{critical}}$=1.48.

Table 5.3: ANOVA of Joint Estimate of KPI Models

Source	**DF**[5]	**Sum Square**	**Mean Square**	$\mathbf{F_{obs}}$
DMI Model				
Regression	34	1.480	0.045	20.87
Residual	123	0.257	0.002	
Total	157	1.737		
RCI Model				
Regression	34	1.085	0.032	3.32
Residual	123	1.183	0.010	
Total	157	2.269		
PCI Model				
Regression	35	2.273	0.065	18.15
Residual	122	0.436	0.004	
Total	157	2.709		
IRI Model				
Regression	35	70.513	2.015	2.56
Residual	122	95.977	0.787	
Total	157	166.490		

[5] Degrees of Freedom.

Table 5.4: Joint Estimate Parameters of Four Models by the SUR Method

	DMI Model		RCI Model		PCI Model		IRI Model	
Parameter	Parameter Estimate	t statistics	Parameter Estimate	t statistics	Parameter Estimate	t statistics	Parameter Estimate	t statistics
β0	2.470	21.650	1.646	6.720	4.536	29.840	1.471	0.660
β1	-0.012	-0.860	0.031	1.020	-0.004	-0.240	-0.281	-1.010
β2	-0.018	-1.750	-0.026	-1.160	-0.026	-1.890	-0.019	-0.100
β3	-0.013	-0.380	-0.023	-0.320	-0.009	-0.190	-2.260	-3.470
β4	-0.018	-0.440	0.046	0.510	-0.011	-0.220	2.421	2.940
β5	-0.016	-0.420	0.018	0.230	-0.020	-0.400	1.788	2.490
β6	0.025	0.830	0.016	0.250	0.041	0.990	-2.399	-4.050
β7	-0.004	-0.310	0.025	0.920	0.004	0.250	-0.104	-0.430
β8	-0.044	-4.670	0.001	0.050	-0.042	-3.420	0.317	1.730
β9	0.008	0.580	-0.007	-0.220	0.005	0.370	-0.100	-0.370
β10	-0.052	-4.380	-0.055	-2.140	-0.070	-4.540	0.288	1.240
β11	0.015	0.850	-0.042	-1.130	-0.006	-0.250	0.150	0.440
β12	-0.034	-2.100	0.002	0.070	-0.027	-1.250	-0.093	-0.290
β13	-0.041	-1.950	-0.031	-0.680	-0.051	-1.780	-0.467	-1.130
β14	0.003	0.100	0.055	0.810	0.024	0.500	0.792	1.280
β15	0.011	0.660	0.051	1.410	0.034	1.500	0.102	0.310
β16	-0.012	-0.970	-0.006	-0.200	-0.018	-0.990	0.098	0.390
β17	0.059	1.200	-0.017	-0.160	0.063	0.990	-0.646	-0.680
β18	-0.105	-1.810	-0.017	-0.140	-0.137	-1.800	0.728	0.650
β19	-0.022	-1.160	-0.067	-1.680	-0.049	-1.950	0.609	1.670
β20	0.013	0.700	0.056	1.380	0.036	1.420	-0.101	-0.270
β21	0.015	0.270	0.064	0.540	0.053	0.690	0.109	0.100
β22	-0.062	-0.670	-0.113	-0.580	-0.117	-0.920	-1.097	-0.620
β23	-0.005	-0.280	-0.042	-1.130	-0.019	-0.870	-0.180	-0.530
β24	-0.013	-1.150	-0.033	-1.340	-0.023	-1.470	0.256	1.130
β25	0.027	0.830	-0.056	-0.820	-0.007	-0.200	0.610	0.970
β26	-0.074	-1.710	-0.001	-0.010	-0.065	-1.130	-0.748	-0.900
β27	-0.014	-0.720	-0.032	-0.780	-0.018	-0.720	-0.790	-2.120
β28	-0.009	-0.480	0.039	0.970	0.003	0.140	0.649	1.790
β29	-0.010	-0.480	0.038	0.860	-0.012	-0.450	-0.003	-0.010
β30	-0.014	-0.760	-0.052	-1.280	-0.022	-0.870	-0.209	-0.570
β33	-0.003	-0.420	-0.012	-0.740	-0.007	-0.730	-0.115	-0.770
β34	-0.005	-0.590	0.029	1.700	0.005	0.580	-0.117	-0.750
β35	-0.004	-0.610	0.033	2.090	0.009	1.010	0.048	0.330
β36	-0.027	-1.290	0.033	0.720	-0.006	-0.280	-0.106	-0.250
β37					0.000	-0.440	0.060	2.52

Table 5.5: ANOVA of KPI Models Estimated by the OLS Approach

Source	DF	Sum Square	Mean Square	F_{obs}
DMI Model				
Regression	34	1.513	0.045	20.72
Residual	123	0.264	0.002	
Total	157	1.767	0.011	
RCI Model				
Regression	34	1.078	0.032	3.24
Residual	123	1.205	0.010	
Total	157	2.273	0.015	
PCI Model				
Regression	35	2.250	0.064	17.78
Residual	122	0.441	0.004	
Total	157	2.720	0.017	
IRI Model				
Regression	35	7.657	0.219	3.94
Residual	122	6.778	0.056	
Total	157	12.070	0.077	

The parameters of severity of shoulder cracking (x_{31}) and extent of shoulder cracking (x_{32}) could not be estimated as most of the ratings of severity and extent are found as "0". Therefore, these two variables are dropped from the estimation of all models. Jointly-estimated parameters by the SUR method of all models are listed in Table 5.4.

After estimating the models by OLS and SUR approaches, all independent variables that have a parameter with a marginal level of significance are considered as significant if:

$|t_{obs}| > t_{critical}$ for significance level, α=0.025 (for 97.5% confidence interval), n-p=122 (for DMI and RCI) or 123 (for PCI and IRI)=1.97

It is noted that in the DMI model, the extent of wheel track rutting, distortion and longitudinal wheel track cracking (single and multiple) are significant variables. For RCI, percentage of trucks and the extent of distortion are significant variables. For PCI, the extent of wheel track rutting and distortion are significant variables. For IRI, severity and extent of flushing, rut depth in mm, severity and extent of rippling and shoving, the severity of longitudinal meandering and mid-lane cracking are significant variables.

It is found that the severity of centreline alligator cracking and transverse alligator cracking have high elasticity on DMI. The extent of pavement edge alligator cracking, the extent of pavement edge (single and multiple) cracking, the extent of longitudinal wheel track alligator cracking, and the severity of centreline (single and multiple) cracking have high elasticity on RCI. The severity of centreline alligator cracking, the severity of pavement edge alligator cracking, the extent of rippling and shoving and the extent of pavement edge (single and multiple) cracking have high elasticity on PCI. The extent of flushing, the severity of rippling and shoving and the extent of longitudinal wheel track alligator cracking have high elasticity on IRI.

Considering the same variables, the models are estimated separately by the OLS approach. ANOVA of KPI Models estimated by the OLS approach is shown in Table 5.5. From Table 5.5, it is found that all the models are statistically significant. From Table 5.3 and Table 5.4, it is found that the jointly-estimated DMI model shows lower sum of squares unexplained by regression or sum of squares of error (SSE) along with lower sum of squares explained by regression (SSR) than that in the DMI model by the OLS approach. The jointly-estimated IRI model shows higher SSR and also higher SSE than that in the OLS approach. The jointly-estimated RCI and PCI models show higher SSR and lower SSE than that in the RCI and PCI models by the OLS approach. Higher SSR and lower SSE show improvement in the model's goodness of fit by joint estimation. However, unobserved random factors explaining the dependent variables may be correlated. If they are correlated, OLS regression will give biased results. If they are not, OLS and SUR would give same parameter estimates.

The parameters of all models estimated by the OLS approach are listed in Table 5.6. In the DMI model, extent of wheel track rutting, the extent of distortion, and extent of longitudinal wheel track cracking (single and multiple) are found as significant variables by the OLS approach, which are also found as significant variables by the SUR approach.

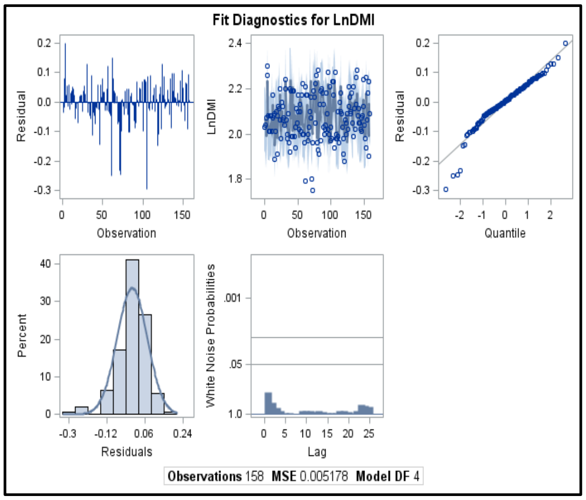
Similarly, the percentage of trucks and the extent of distortion are found as significant variables in the RCI model by both approaches. In using the OLS approach in the PCI model, the severity of pavement edge (single and multiple) cracking is found to be significant, whereas the extent of wheel track rutting and the extent of distortion is significant in the SUR approach. For the IRI model, the severity of centreline (single and multiple) cracking is the significant variable. However, in the jointly-estimated IRI model, the severity and extent of flushing, rut depth, the severity and extent of rippling and shoving and the severity of longitudinal meandering and mid-lane cracking are the significant variables. Joint estimation in the SUR approach takes care of the influences of correlated unobserved explanatory variables. Such effects are not separated in the OLS method and may be compounded with other estimates. For this reason, the significance of explanatory variables can be different in the two approaches.

Table 5.6: Parameter Estimate of Four Models Separately by OLS Approach

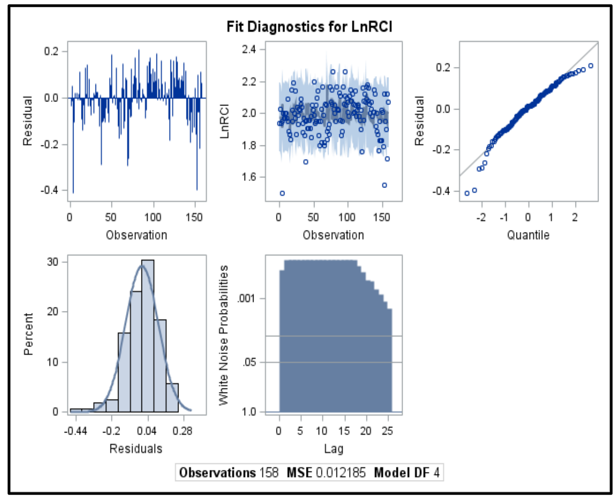
Parameters	DMI Model		RCI Model		PCI Model		IRI Model	
	Parameter Estimate	t_{obs}	Parameter Estimate	t_{obs}	Parameter Estimate	t_{obs}	Parameter Estimate	t_{obs}
β0	2.480	21.420	1.644	6.648	4.523	29.780	0.914	1.536
β1	-0.013	-0.894	0.032	1.031	-0.004	-0.228	-0.143	-1.949
β2	-0.019	-1.806	-0.025	-1.133	-0.026	-1.899	0.054	1.013
β3	-0.012	-0.355	-0.023	-0.316	-0.008	-0.189	-0.021	-0.119
β4	-0.020	-0.463	0.047	0.517	-0.013	-0.235	-0.012	-0.055
β5	-0.018	-0.474	0.017	0.212	-0.014	-0.293	0.217	1.138
β6	0.027	0.877	0.017	0.257	0.036	0.906	-0.299	-1.902
β7	-0.004	-0.298	0.025	0.906	0.004	0.239	-0.045	-0.696
β8	-0.045	-4.703	0.001	0.064	-0.042	-3.413	0.020	0.414
β9	0.008	0.540	-0.006	-0.185	0.008	0.403	0.078	1.054
β10	-0.052	-4.338	-0.055	-2.151	-0.072	-4.572	0.088	1.410
β11	0.014	0.808	-0.041	-1.085	-0.005	-0.229	0.111	1.232
β12	-0.034	-2.051	0.001	0.038	-0.027	-1.255	0.011	0.128
β13	-0.041	-1.904	-0.033	-0.721	-0.050	-1.786	0.059	0.531
β14	0.002	0.066	0.058	0.853	0.021	0.496	-0.161	-0.977
β15	0.013	0.782	0.050	1.366	0.034	1.522	-0.189	-2.140
β16	-0.014	-1.111	-0.005	-0.190	-0.017	-0.998	0.023	0.343
β17	0.058	1.173	-0.016	-0.152	0.061	0.952	-0.055	-0.219
β18	-0.106	-1.801	-0.018	-0.143	-0.133	-1.749	0.097	0.326
β19	-0.023	-1.212	-0.066	-1.643	-0.048	-1.923	0.163	1.685
β20	0.014	0.758	0.054	1.328	0.036	1.444	-0.137	-1.405
β21	0.016	0.277	0.063	0.524	0.050	0.683	-0.184	-0.641
β22	-0.062	-0.673	-0.113	-0.568	-0.113	-0.932	0.367	0.774
β23	-0.005	-0.298	-0.042	-1.111	-0.021	-0.908	0.109	1.205
β24	-0.012	-0.987	-0.033	-1.330	-0.022	-1.421	0.098	1.637
β25	0.025	0.779	-0.054	-0.772	-0.009	-0.210	0.062	0.370
β26	-0.072	-1.660	-0.004	-0.038	-0.064	-1.129	0.088	0.398
β27	-0.014	-0.703	-0.034	-0.821	-0.019	-0.749	0.006	0.062
β28	-0.009	-0.472	0.041	1.015	0.003	0.140	-0.013	-0.136
β29	-0.011	-0.528	0.036	0.803	-0.012	-0.433	-0.037	-0.345
β30	-0.013	-0.700	-0.050	-1.233	-0.021	-0.846	0.048	0.498
β33	-0.003	-0.444	-0.012	-0.742	-0.007	-0.694	0.010	0.252
β34	-0.005	-0.616	0.029	1.696	0.007	0.616	-0.034	-0.814
β35	-0.005	-0.655	0.033	2.118	0.010	1.027	-0.050	-1.296
β36	-0.028	-1.325	0.032	0.700	-0.009	-0.312	-0.107	-0.971
β37					-0.001	-0.511	-0.002	-0.288

Table 5.7: Revised KPI Models with Significant Variables

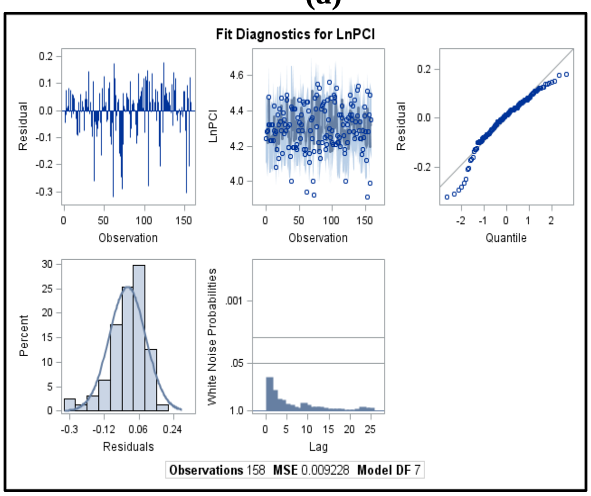
	SUR Method		OLS Approach	
Variable	**Parameter Estimate**	**t statistics**	**Parameter Estimate**	**t statistics**
	DMI Model			
β0	2.234	169.540	2.258	163.640
β8	-0.066	-8.720	-0.057	-6.970
β10	-0.075	-7.120	-0.066	-6.220
β12	-0.019	-2.730	-0.064	-5.840
	RCI Model			
β0	1.999	71.290	1.955	54.840
β35	0.026	2.810	0.045	3.380
β10	-0.072	-4.230	-0.077	-4.460
β38	-0.017	-2.090	-0.018	-2.070
	PCI Model			
β0	4.490	240.720	4.568	180.160
β8	-0.070	-8.750	-0.075	-6.550
β10	-0.098	-6.940	-0.090	-6.050
	IRI Model			
β0	0.243	1.500	0.236	1.460
β37	0.062	3.030	0.062	3.000
β3	-1.680	-3.060	-1.690	-3.080
β4	1.886	2.730	1.897	2.740
β5	1.361	2.320	1.379	2.350
β6	-2.096	-4.110	-2.112	-4.140



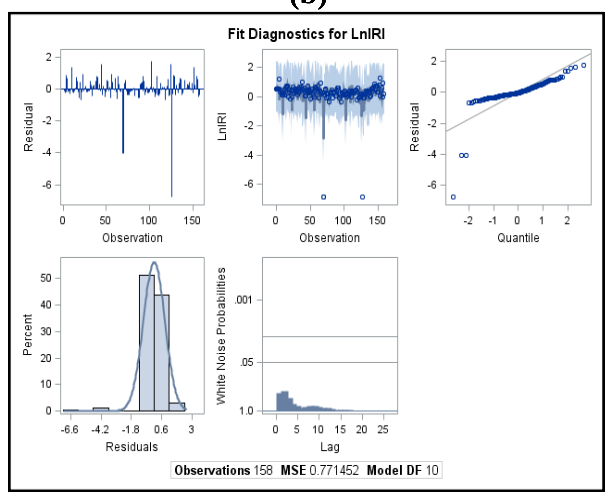
(a)



(b)



(c)



(d)

Figure 5.1: Diagnostics of 'Goodness Fit' of Revised Models (a) Ln DMI model, (b) Ln RCI Model, (c) Ln PCI Model, and (d) Ln IRI Model

Considering these significant variables only, all four models are further revised and the SUR method is applied again. Since IRI is also a distress and used to estimate other KPIs (RCI and PCI), it is considered as an additional variable in the revised model as *x38*. To ensure the results are compared in a straightforward manner, the models are also estimated by the OLS approach and consider the significant variables found from the SUR method. The estimated parameters of the revised models are listed in Table 5.7. Improved goodness of fit of the revised models estimated by the SUR approach are presented in Figure 5.1. In Table 5.7, it is evident that these variables are significant in both approaches. However, the estimated value of parameters differs slightly. This is expected because the SUR method skims out the compounded effects of the correlated unobserved explanatory variables.

Table 5.8: Covariance and Correlation Matrix of Residuals in Jointly-Estimated Models

Covariance Matrix				
	Ln DMI	Ln RCI	Ln PCI	Ln IRI
Ln DMI	0.0021	0.0001	0.0020	-0.0034
Ln RCI	0.0001	0.0096	0.0039	-0.0150
Ln PCI	0.0020	0.0039	0.0036	-0.0097
Ln IRI	-0.0034	-0.0150	-0.0097	0.7867
Correlation Matrix				
	Ln DMI	Ln RCI	Ln PCI	Ln IRI
Ln DMI	1.0000	0.0324	**0.7415**	-0.0834
Ln RCI	0.0324	1.0000	**0.6683**	-0.1724
Ln PCI	**0.7415**	**0.6683**	1.0000	-0.1836
Ln IRI	-0.0834	-0.1724	-0.1836	1.0000

Covariance and correlation matrix models are shown in Table 5.8. From the correlation matrix, it is found that unobserved factors in the PCI model are highly correlated to the DMI (correlation coefficient is 0.74) and RCI models (correlation coefficient is 0.67). However, unobserved factors in the IRI model are not highly correlated (correlation coefficients are 0.083, 0.17 and 0.18 between DMI, RCI and PCI) to any other models. Since the IRI value measured by the automated device is used in the model, unobserved factors in the IRI may not be correlated to other estimated models based on individual distresses.

5.4 Chapter Summary

In this chapter, regression models for KPI predictions are estimated by using the SUR approach. The prediction models are generally estimated by using the OLS approach. However, the OLS approach may result in biased estimates if unobserved factors influencing different KPIs are correlated. For this reason, a statistically rigorous methodology within the SUR approach was used to estimate coefficients jointly as opposed to an equation-by-equation approach.

As discussed, in Ontario, KPI models are developed from road condition surveys for specifically selected distresses. These models are developed based on the weightage of such distresses that are evaluated or rated in a subjective manner. However, the average subjective rating is only recorded in the MTO PMS-2 database. The multiple raters' ratings are not available to analyze the subjective variability. To accommodate that subjective ratings may have variability, but unobserved in the recorded data set, the SUR approach is considered. The model can only accommodate the effects of such variability on parameter estimates, but quantifying the extent of variability is impossible.

Although the SUR approach is used to estimate the models, the OLS approach is also used to compare the results by both approaches in a straightforward way. All models are significant in both approaches. All independent variables that have a parameter with a marginal level of significance are considered as significant. Similar significant variables are found in the DMI and RCI models in both approaches. However, different significant variables are found in the IRI and PCI models. Revised models that consider only significant variables show the difference in parameter estimates of both approaches. This is expected because the SUR approach skims out compounded effects of correlated unobserved factors affecting pavement performance. Since OLS and SUR are not providing the same parameter estimates, the unobserved random variables are considered to be correlated. Therefore, the SUR approach is preferable.

It is found that unobserved factors in the PCI model are highly correlated to those in the DMI and RCI models. In the SUR approach, the efficiency of estimation increases with higher correlation among the random error terms of the different equations. It also considers the effects of larger sample sizes and multi-collinearity between the regressors. For this reason, efficient estimations of models, with highly correlated unobserved factors and large road networks, such as Ontario highways, require joint estimation rather than OLS.

The joint estimation of KPI models is an effective methodology to estimate performance indices. That being said, the results of the analyses can facilitate decision-making in a PMS with appropriate performance pavement predictions. As such, the benefit is related to the effective M&R implementation and resource allocation in a PMS.

In this chapter, the analysis establishes the requirement of using joint estimation to estimate performance model indices. This approach will be carried out in Chapter 8, while estimating KPI models based on predicted distresses by the M-E approach.

Chapters 4 and 5 mainly focused on the existing performance indices in practice, influencing variables affecting performance and the impact of section lengths on overall management. However, the next chapters will focus on the prediction of distresses based on the M-E approach and the estimation of the performance index based on those predicted distresses.

CHAPTER 6
APPLICATION OF THE MECHANISTIC-EMPIRICAL APPROACH: SENSITIVITY ANALYSIS

The M-E analysis considers three-level hierarchical inputs to predict performance in terms of IRI, permanent deformation or rut depth, total cracking (reflective and alligator), AC thermal fracture, AC bottom-up fatigue cracking and AC top-down fatigue cracking. However, these inputs with different levels of accuracy may have a significant impact on performance predictions. Before predicting the distresses, identifying the important inputs of MEPDG software (AASHTOWare Pavement M-E) will ensure efficient analysis. This chapter focuses on the sensitivity of inputs of the MEPDG distresses based on an experimental design to identify the requirements of the accuracy level of inputs.

The work presented in this chapter is published in the International Journal of Pavement Engineering (IJPE) (Jannat 2015). Part of this chapter was also presented at the Transportation Association of Canada (TAC) Conference (Jannat 2014).

6.1 Introduction

As discussed in Chapter 1, the MEPDG was developed in 2004 to address the shortcomings of empirical pavement design methods (NCHRP 2004, and AASHTO 2008). The MEPDG distress prediction models are developed by using the Long-Term Pavement Performance (LTPP) data, which includes pavement sections of many U.S. states and Canadian provinces. The recommendations related to the level of accuracy and required quality of the input variables are outlined in the AASHTO guide (AASHTO 2010). However, it is necessary to analyze the requirements to efficiently obtain accuracy at Level 1 for all inputs. It would otherwise not be efficient to put effort for a higher level of accuracy. For this reason, a sensitivity analysis is essential to identify important inputs that have significant impacts on the predicted distresses.

This chapter investigates the effect of inputs on the predicted distresses based on the M-E approach to identify the accuracy-level requirements for precise prediction. From different levels of the selected inputs and for the statistical validity of investigations, an experimental design-based approach is used. For the main effect, local sensitivity is carried out, and for interaction effects, experimental design is formed based on a random combination of variables. The normalized values (divided by the mean value of the corresponding variable) of the variables within the regression model provide the relative influences of different input variables on MEPDG distresses.

6.2 Accuracy Levels of Inputs

The input data required for the AASHTOWare Pavement M-E analysis are mainly related to traffic, climate, pavement structure and material properties. The accuracy levels of inputs available for the M-E analysis are described in the Chapter 3.

The input data are mainly collected from the MTO-PMS-2 database, project specific information and default values from the AASHTOWare Pavement M-E Design Interim Report (MTO 2012).

6.3 Experimental Design

A sensitivity analysis is conducted to investigate relative influences of input variables. Generally, sensitivity analysis designs are categorized into three classes: screening methods, local sensitivity analysis and global sensitivity analysis (Graves 2011).

A screening method focuses on the hierarchical ranking according to the importance of input variables, rather than providing change in quantity or impact on output. Local sensitivity focuses on the local impact of inputs on the performance of outputs. This method is conducted by varying certain inputs, while keeping other inputs constant. Global sensitivity analysis is carried out by varying the inputs over the entire input variables.

The inputs may have the independent (main) and/or combined (interaction) effects on distress outputs.

6.3.1 Experimental Design for Main Effects

Since the independent influence of an input variables defines its required accuracy level, local sensitivity is considered as a suitable method. Local sensitivity will identify the requirements for a higher level of accuracy, which is a significant step in predicting distresses, especially for selecting the properties relevant to local materials and traffic. Moreover, this method will investigate independent influence, since the experimental sets are independent. Thus, local sensitivity analysis based on experimental design-based methods will be suitable to identify the individual effect of inputs.

The base section (overlay design of highway sections with a performance cycle of eight years, three overlay layers, sub-base: granular A, base: granular B1 and subgrade: sandy silt) is selected after analyzing the performances if predicted distresses are close to the observed performances. Figure 6.1 shows the performance curve for PCI, IRI and permanent deformation of the base case road section.

For each input variable, specific ranges from the base case are selected based on the nature of the input. The ranges are selected based on the historical performance record (existing condition, traffic information, subgrade type, layer thickness etc.) of pavement sections from MTO-PMS-2, Ontario's default values (axle per truck, axle-load spectra and default materials properties for specific AC, base and subgrade etc.) from 'Ontario's Default Parameters for AASHTOWare Pavement M-E Design- Interim Report' (MTO 2012) and soil properties and specifications from the Pavement Asset Design and Management Guide (PADMG) (TAC 2013). Table 6.1 summarizes the range of change in input values considered in this analysis.

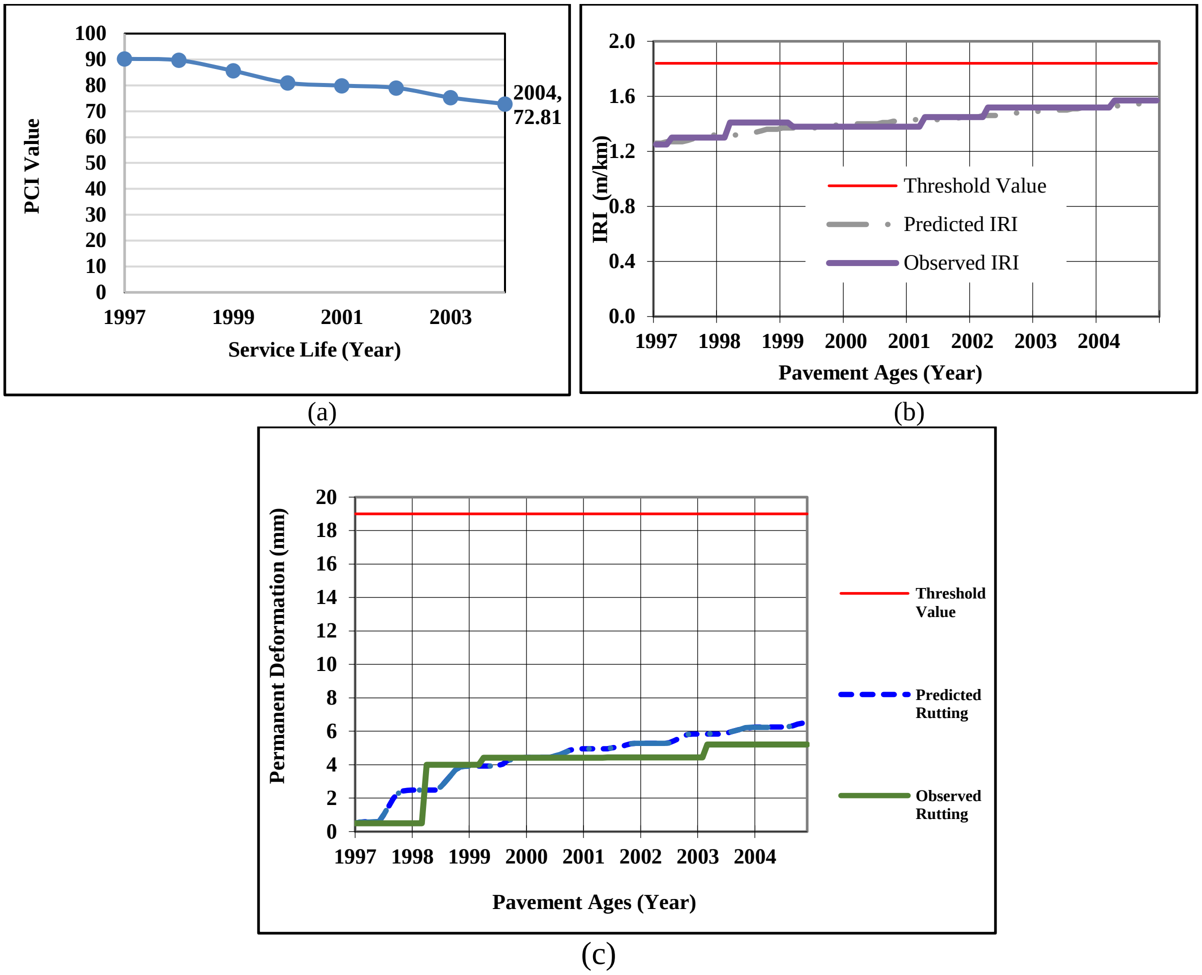


Figure 6.1: (a) Performance Curve of Base Case as per PCI; (b) Comparison of Observed IRI to Predicted IRI; (c) Comparison of Observed to Predicted Permanent Deformation

After observing the effects on specific distresses of all input variables, a total of 46 independent variables are considered for the analysis. The levels are found to be different for each independent input variable, since the ranges of the levels are different. Finally, an experimental design is used to identify a total of 171 experimental sets, considering 46 independent variables.

Table 6.1: Summary of Ranges of Input Variables

Input Category	Input	% Change in Input Comparing to Base Value	Remarks
Existing Condition	Initial IRI	-40% to + 40%	Considering the target value (1.9 m/km for freeways and 2.3 m/km for Arterials) of IRI for Ontario, the range of change in initial IRI of base case is selected. A total of 9 levels are considered from -40% to +40% with 10% increment.
	Initial Permanent Deformation	-50% to + 50%	Considering the target value of Permanent deformation of 19 mm for Ontario, the range of change in existing permanent deformation of base case is selected. A total of 11 levels are considered from -50% to +50% with 10% increment.
	Milled Thickness	40 mm to maximum 100 mm	From the historical record, 40 mm to 100 mm milled thickness are found. The ranges are selected from 40 mm to 100 mm with increment of 20 mm. A total of 4 levels are considered.
Traffic	Annual Average Daily Truck Traffic (AADTT)	-50% to + 50%	From the historical record of AADTT of all road sections, the ranges are selected from 700 to 2109 with increment of 10%. A total of 11 levels are considered.
	Percent Truck in Design Lane	-25% to + 11%	From the default value of percent of truck in design lane based on the number of lanes in one direction and AADT in both direction, the ranges are selected from 60% to 100% with increment of 10%. A total of 9 levels are considered.
	Traffic Growth Factor	-50% to + 50%	From the annual historical record of AADT, the compound growth factors are calculated for all road sections. The ranges are selected from 1.65% to 4.94% with increment of 10% which are -50% to +50% of base case value. A total of 11 levels are considered.
	Operational Speed	-40% to + 40%	Considering the speed limit of highways, the ranges are selected from min 60 km to max 140 km with increment of 10% which are -40% to +40% of base case value. A total of 9 levels are considered.
	Axle per Truck	Default Value of Southern Ontario, Northern Ontario and Ontario 2006	Default value of Southern Ontario, Northern Ontario and Ontario 2006 value are considered as 3 independent variables with level 1.
	Truck Traffic Class (TTC)	TTC type 1 to 17	Types of TTC are defined based on 17 combination of %bus, % single trailer truck, and % multi trailer truck. Each type is considered as an independent variable with level of 1.

Input Category	Input	% Change in Input Comparing to Base Value	Remarks
	Axle Load Spectra	Default Value of Southern Ontario, Northern Ontario, Ontario 2006 and Software Default Value	Based on default value of Southern Ontario, Northern Ontario and Ontario 2006 value. In addition, software default value is considered and a total of 4 independent variables each with single level are considered.
Climate	Water Table Depth	-60% to + 60%	Based on Ontario default value of 6.1 m, ranges are selected from 2.44 to 9.76 m. A total of 7 levels are considered from -60% to +60% with a 20% increment.
AC Layer and Properties	Top Layer Thickness	-49% to + 50%	Considering the minimum thickness requirement of the software of 25.4 mm and historical record of average overlay top layer thickness, the range is selected from 25.4 mm to 75 mm. A total of 11 levels ranging -49% to +50% of base case with an increment of 10%, are considered.
	Unit Weight	-23% to +3%	Based on Ontario default value of volumetric properties of AC, the ranges are selected from 1940 to 2596 KG/M3. A total of 6 levels are considered from -23% to +3%.
	Effective Binder Content	-59.7% to +20%	Based on Ontario default value of volumetric properties of AC, effective binder content ranges unto 14.88 %. A total of 5 levels are considered from -59.7% to +20% of base value 12.70%.
	Air Voids	-40% to +60%	Based on Ontario default value of volumetric properties of AC for selected sections, air voids range from 2.4% to 5%. A total of 6 levels are considered from -40% to +60% of base value 4%.
	Reference Temperature	-30% to +23%	Ontario default value of reference temperature is 21.1 degree Celsius However; reference temperature is varied from -30% to 23% of 21.1 degree Celsius. A total of 5 levels are considered.
	Thermal Conductivity	-30% to +120%	Ontario default value of thermal conductivity 1.16 watt/meter-kelvin. However, a total of 6 levels are considered ranging from -30 to +120% of 1.16 watt/meter-Kelvin.
	Heat Capacity	-40% to +40%	Ontario default value of heat capacity is 963 joules/kg-Kelvin. However, a total of 5 levels are considered ranging from -40% to +40% of 963 joule/kg-Kelvin.
	Asphalt Binder Penetration Grade	Software default value: 40-50, and 60-70; Southern Ontario: 85-100; NE Ontario: 120-150; and NW Ontario: 200-300	Default value for Southern Ontario is 85-100; for NE Ontario is 120-150; for NW Ontario is 200-300. In addition, 40-50 and 60-70 are also considered. A total of 5 subcategories are considered as independent variables with level of 1.

Input Category	Input	% Change in Input Comparing to Base Value	Remarks
Base Layer and Materials	Base Layer Thickness	-40% to +40%	Minimum thickness of base layer for Ontario is 150 mm. Maximum range is considered based on the existing layer thickness of road sections. AASHTO has also guidelines for minimum base layer based on Equivalent Single Axle Load (ESAL). These AASHTO recommended value is also considered here. A total of 9 levels are considered ranging from -40% to +40% of base value 150 mm.
	Resilient Modulus of Base Layer	-60% to +60%	Based on the MR values for types of base materials, the range from 100 MPa to 400 MPa is selected and a total of 7 levels are considered.
Subgrade Materials	Resilient Modulus of Subgrade Soil	-40% to +40%	Based on the corresponding resilient modulus of available subgrade soil types, the range from 25 MPa to 40 MPa is selected. A total of 7 levels are considered for the selected range of -40% to +40% of 35 MPa base value with an increment of 10%.

Table 6.2: MEPDG Outputs Distresses and Target Value of Failure in Ontario

Distress Type	Target Value for Freeway	Target Value for Arterial
Terminal IRI (m/km)	1.9	2.3
Permanent Deformation - Total Pavement (mm)	19	19
Total Cracking (Reflective + Alligator) (%)	100	100
AC Thermal Fracture (m/km)	190	190
AC Bottom-Up Fatigue Cracking (%)	10	20
AC Top-Down Fatigue Cracking (m/km)	380	380
Permanent Deformation - AC Only (mm)	6	6

6.3.2 Experimental Design for Interaction Effects

The input variables may also have interaction effects on distress outputs. For this reason, a combination of input variables is also considered to identify the sensitive combination of input variables. The full factorial experimental design with the selected 46 independent variables and the ranges of selected levels form a large number of experimental sets which may not be efficient. For this reason, only the sensitive input variables found from the main effect analyses are considered to identify the interaction effects. The experimental sets are formed by taking random combinations of input variables. Finally, an experimental design is used with a total of 58 experimental sets. These variables are also normalized.

Table 6.3: Changes in Distress for Respective Change in AADTT

Change in Input AADTT		**Change in Output Distresses**											
AADTT changed by %	**Changed AADTT**	**Terminal IRI (m/km)**	**Change in Terminal IRI (%)**	**Permanent Deformation - Total pavement (mm)**	**Change in Permanent Deformation Total (%)**	**Total Cracking (Reflective + Alligator) (%)**	**AC Thermal Fracture (m/km)**	**Change in AC Thermal Fracture (%)**	**AC Bottom-Up Fatigue Cracking (%)**	**AC Top-Down Fatigue Cracking (m/km)**	**Change in AC Top-Down Fatigue Cracking (%)**	**Permanent Deformation - AC only (mm)**	**Change in Permanent Deformation - AC only (%)**
-50%	703	1.52	-2.56%	5.12	-21.59%	28.32	14.64	0.00%	0	0.01	-66.67%	1.75	-31.37%
-40.%	844	1.53	-1.92%	5.46	-16.39%	28.32	14.64	0.00%	0	0.02	-33.33%	1.93	-24.31%
-30%	984	1.54	-1.28%	5.76	-11.79%	28.32	14.64	0.00%	0	0.02	-33.33%	2.10	-17.65%
-20%	1125	1.54	-1.28%	6.04	-7.50%	28.32	14.64	0.00%	0	0.02	-33.33%	2.26	-11.37%
-10%	1265	1.55	-0.64%	6.29	-3.68%	28.32	14.64	0.00%	0	0.03	0.00%	2.41	-5.49%
Base	1406	1.56	0.00%	6.53	0.00%	28.32	14.64	0.00%	0	0.03	0.00%	2.55	0.00%
10%	1547	1.56	0.00%	6.76	3.52%	28.32	14.64	0.00%	0	0.04	33.33%	2.68	5.10%
20%	1687	1.57	0.64%	6.97	6.74%	28.32	14.64	0.00%	0	0.04	33.33%	2.81	10.20%
30%	1828	1.57	0.64%	7.17	9.80%	28.32	14.64	0.00%	0	0.05	66.67%	2.93	14.90%
40%	1968	1.58	1.28%	7.35	12.56%	28.32	14.64	0.00%	0	0.06	100.00%	3.05	19.61%
50%	2109	1.58	1.28%	7.53	15.31%	28.32	14.64	0.00%	0	0.06	100.00%	3.16	23.92%

6.4 Sensitivity Analysis

For these experiments, the distresses are predicted for 171 experimental sets for main effects and 58 experimental sets for interaction effects using the AASHTOWare Pavement M-E software. The predicted values of each distress are compared to the corresponding target values of failure shown in Table 6.2. The rate of change in output distresses are compared for both experimental sets.

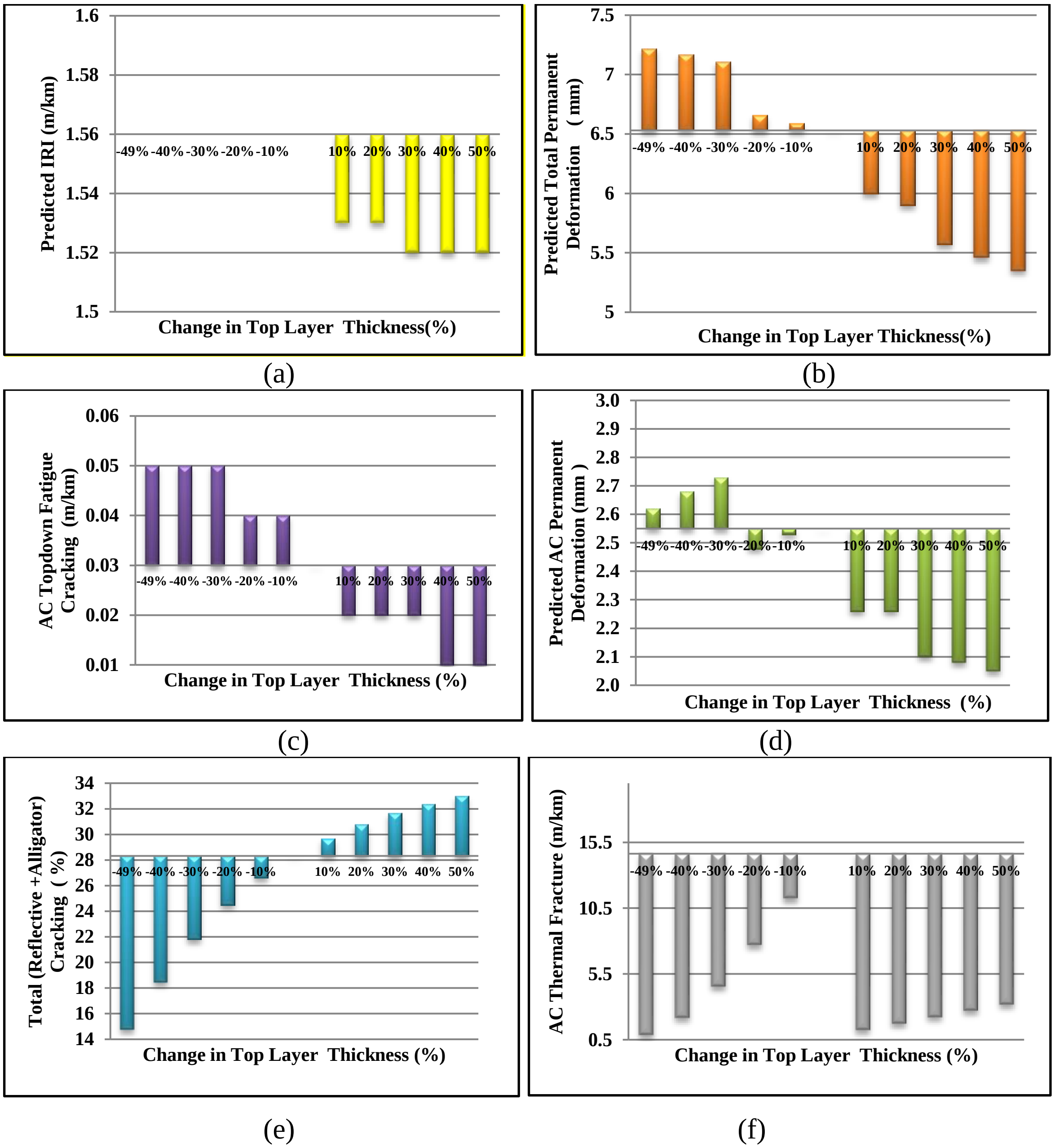


Figure 6.2: Sensitivity of (a) Terminal IRI; (b) Total Permanent Deformation (c) AC Top down Fatigue Cracking; (d) AC Permanent Deformation, (e) Total (Reflective +Alligator) Cracking, (f) AC Thermal Fracture, with Respect to Top Layer Thickness

Table 6.4: Summary of Changes in Distresses for Change in Major Inputs (Main Effect)

Input Variables	Change in Input Parameters Compared to Base Value	Change in Output Distresses						
		Terminal IRI	Total Permanent Deformation	AC Permanent Deformation	Total Cracking (Reflective + Alligator)	AC Thermal Fracture	AC Bottom-Up Fatigue Cracking	AC Top-Down Fatigue Cracking
Initial IRI	-40% to +40%	-32% to +32%	0% to +15%	0% to +15%	0[6]%	0[7]%	0[8]%	0[9]%
Initial Permanent Deformation	-50% to +50%	+4.5% to -2.56%	+48% to -22%	+7% to -5.5%	0%	0%	0%	0%
Milled Thickness	40mm to 100mm max.	+0.64% to +1.28%	+7% to +15%	+11% to +26%	0%	0%	0%	0%
AADTT	-50% to +50%	-2.56% to +1.28%	-22% to +15%	-31% to +24%	0%	0%	0%	-66% to +100%
Percentage of Trucks in the Design Lane	-25% to +11%	-1.28% to +0%	-9% to +4%	-14% to +5%	0%	0%	0%	-33% to +33%
Traffic Growth Factor	-50% to +50%	-0.64% to +0%	-2% to +2%	-3% to +3%	0%	0%	0%	0% to +33%
Operational Speed	-40% to +40%	+0.64% to -0.64%	+0.64% to -3.83%	+8.6% to -5.5%	0%	0%	0%	33% to +0%
Axle Per Truck	3 Types	0%	+0.15% to 0.31%	+0% to -1.81%	0%	0%	0%	0%
Truck Traffic Class (TTC)	TTC Type 1-17	-0.64% to -3.21%	-1.23% to -27.57%	Varies from -1.26% to -26.27%; for Type 3 +0.98%; for Type 5 1.96%	0%	0%	0%	-33% to -66%
Axle-Load Spectra	4 Types	-0.64% to +0.64%	-0.92% to +5.51%	1.18% to -7.06%	0%	0%	0%	+33% to 0%
Water Table Depth	-60% to +60%	0%	0%	0%	0%	0%	0%	0%
Top-Layer Thickness	-49% to +50%	0.0% to - 2.56%	10.57% to -18.07%	-23% to -94%	-48% to +17%	2.75% to -19.6%	0%	+66% to -66%

[6] 0% = No change in respective output distress due to change in input

[7] 0% = No change in respective output distress due to change in input

[8] 0% = No change in respective output distress due to change in input

[9] 0% = No change in respective output distress due to change in input

Input Variables	Change in Input Parameters Compared to Base Value	Change in Output Distresses						
		Terminal IRI	**Total Permanent Deformation**	**AC Permanent Deformation**	**Total Cracking (Reflective + Alligator)**	**AC Thermal Fracture**	**AC Bottom-Up Fatigue Cracking**	**AC Top-Down Fatigue Cracking**
Unit Weight	-23% to +3%	0%	0.92% to - 0.15%	+2.35% to -0.39%	0%	+44% to -6.32%	0%	0%
Effective Binder Content	-59.7% to +20%	14.74% to -0.64%	-9.04% to +1.53%	-12.16% to +1.96%	0%	+25.12% to -74%, failure found for -40% to -59.7% change in input	0%	+1633.33% to - 33.33%; values are lower than the failure criteria 380 m/km
Air Voids	-40% to +60%	-0.64% to +5.13%	-1.53% to +3.68%	-2.35% to +4.71%	0%	140% for - 40% change in input; varies - 19.19% to 836.75%for -20% to +60% of input change	0%	-66.67% to +666.67%; the values are lower than the failure criteria of 380m/km
Reference Temperature	-30% to +23%	0%	0%	0%	0%	0%	0%	0%
Thermal Conductivity	-30% to +120%	-0.64% to 0%	-2.30% to +3.83%	-3.92% to +7.06%	0%	-18.24% to +18.78%	0%	0% to +33.33%
Heat Capacity	-40% to +40%	+0.64% to -0.64%	+1.53% to - 1.53%	+3.53% to - 3.53%	0%	+89.48% to -48.77%	0%	0%
Asphalt Binder Penetration Grade	5 types	+8.33% to 0%	-7.50% to +10.41%	-12.16% to +18.04%	0% to +0.35%	+14.95% to -100%; failure found for 40-50 and 60-70	0%	0%
Base-Layer Thickness	-40% to +40%	0% to -0.64%	4.29% to - 1.07%	-4.71% to +1.57%	0%	+17.96% to +3.42%	0%	0%
Resilient Modulus of Base Layer	-60% to +60%	+0.64% to -0.64%	+6.28% to - 3.52%	-3.14% to +1.57%	0%	0%	0%	+33.33% to 0%
Resilient Modulus of Subgrade Soil	-40% to +40%	+2.56% to -1.28%	+29.86% to - 12.40%	-2.35% to -1.18%	0%	0%	0%	0% to +33.33%

Table 6.5: Summary of Sensitive Inputs (Main Effect) as per Range of Change in Output Distresses

Output Distress	Sensitive Inputs as per Change in Output Distresses
Terminal IRI	Initial IRI, AC Effective Binder Content, Air Voids, Initial Permanent Deformation, AADTT, Subgrade Resilient Modulus, AC Top-Layer Thickness, Milled Thickness, Percentage of Trucks in the Design Lane, Operational Speed, Asphalt Binder Penetration Grade, Traffic Growth Factor, TTC Types and Axle-Load Spectra
Total Permanent Deformation	Initial Permanent Deformation, Subgrade Resilient Modulus, TTC Types, AADTT, AC Top-Layer Thickness, Asphalt Binder Penetration Grade, Milled Thickness, Initial IRI, Percentage of Trucks in the Design Lane, Percentage of Effective Binder Content, Resilient Modulus of Base Layer, Base-Layer Thickness, 13. Operational Speed
AC Permanent Deformation	AC Top-Layer Thickness, AADTT, TTC Class, Percentage of Trucks in the Design Lane, Milled Thickness, Initial IRI, Effective Binder Content, Binder Penetration Grade, Operational Speed, Axle-Load Spectra, AC Thermal Conductivity, Initial Permanent Deformation, Air Voids, Base-Layer Thickness and AC Heat Capacity
Total Cracking (Reflective + Alligator)	AC Top-Layer Thickness and Asphalt Binder Penetration Grade
AC Thermal Fracture	Effective Binder Content, AC Binder Penetration Grade, AC Air Voids, AC Heat Capacity, AC Unit Weight, AC Top-Layer Thickness, AC Thermal Conductivity and Base-Layer Thickness
AC Top-Down Fatigue Cracking	Effective Binder Content, AC Air Voids, AADTT, TTC Types, AC Top-Layer Thickness, Percentage of Trucks in the Design Lane, Subgrade Resilient Modulus, AC Thermal Conductivity, Traffic Growth Factor, Axle-Load Spectra and Resilient Modulus of Base Layer

6.4.1 Sensitivity Analysis for Main Effects

The rate of changes in output distresses are plotted for 46 input variables to be compared. For example, Table 6.3 shows the changes in distresses due to changes in AADTT and Figure 6.2 shows the changes in major sensitive distresses due to changes in AC top-layer thickness. Finally, changes in all output distresses and input variables are summarized in Table 6.4.

After comparing the range of change in output distresses to a range of change in inputs, the inputs with substantial effects on distresses are screened and listed in Table 6.5. A multiple linear regression analysis is carried out by considering the sensitive inputs, listed in Table 6.5, for six major distresses separately. For example, for IRI, regression analysis is conducted for the following sensitive variables.

At first, the following regression model of Terminal IRI is shown by considering the 2nd order term:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_1^2 + \beta_{12} X_2^2 + \beta_{13} X_3^2 + \beta_{14} X_4^2 + \beta_{15} X_5^2 + \beta_{16} X_6^2 + \beta_{17} X_7^2 + \beta_{18} X_8^2 + \beta_{19} X_9^2 + \beta_{20} X_{10}^2 + \beta_{21} X_1X_2 + \beta_{22} X_1X_3 + \beta_{23} X_1X_4 + \beta_{24} X_1X_5 + \beta_{25} X_1X_6 + \beta_{26} X_1X_7 + \beta_{27} X_1X_8 + \beta_{28} X_1X_9 + \beta_{29} X_1X_{10} + \beta_{30} X_2X_3 + \beta_{31} X_2X_4 + \beta_{32} X_2X_5 + \beta_{33} X_2X_6 + \beta_{34} X_2X_7 + \beta_{35} X_2X_8 + \beta_{36} X_2X_9 + \beta_{37} X_2X_{10} + \beta_{38} X_3X_4 + \beta_{39} X_3X_5 + \beta_{40} X_3X_6 + \beta_{41} X_3X_7 + \beta_{42} X_3X_8 + \beta_{43} X_3X_9 + \beta_{44} X_3X_{10} + \beta_{45} X_4X_5 + \beta_{46} X_4X_6 + \beta_{47} X_4X_7 + \beta_{48} X_4X_8 + \beta_{49} X_4X_9 + \beta_{50} X_4X_{10} + \beta_{51} X_5X_6 + \beta_{52} X_5X_7 + \beta_{53} X_5X_8 + \beta_{54} X_5X_9 + \beta_{55} X_5X_{10} + \beta_{56} X_6X_7 + \beta_{57} X_6X_8 + \beta_{58} X_6X_9 + \beta_{59} X_6X_{10} + \beta_{60} X_7X_8 + \beta_{61} X_7X_9 + \beta_{62} X_7X_{10} + \beta_{63} X_8X_9 + \beta_{64} X_8X_{10} + \beta_{65} X_9X_{10} \quad (6.1)$$

Where,
y = Terminal IRI
X_1= Existing Initial IRI
X_2= Existing Initial Permanent Deformation,
X_3= Top-Layer Thickness of AC
X_4= Effective Binder Content in AC
X_5= Air Voids in AC (%)
X_6= Existing Milled Thickness
X_7= Resilient Modulus of Subgrade Soil
X_8= Annual Average Daily Truck Traffic (AADTT)
X_9= Percentage of Trucks in the Design Lane
X_{10}= Operational Speed of Vehicles
β_o …………β_{10} = Coefficients

This model is not found as significant as $F_{observed}$ (0.215) <$F_{critical}$ (2.2147). For this reason, in the next step, the IRI model is revised by considering only 1st order variables.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} \quad (6.2)$$

After regression analysis, the 1st revised model is found as:

$$y = 0.56069 + 0.940841X_1 - 0.019386X_2 - 0.000333X_3 - 0.014764X_4 + 0.018594X_5 - 0.000335X_6 - 0.002949X_7 + 0.000042X_8 + 0.001863X_9 - 0.000649X_{10} \quad (6.3)$$

Table 6.6: ANOVA of the 1st Revised Model of Terminal IRI

	df	**SS**	**MS**	**F**
Regression	10	2.773	0.277	26.285
Residual	69	0.728	0.011	
Total	79	3.499		

The ANOVA calculation of the 1st revised model (equation 6.3) is shown in Table 6.6. A significance test of the model is carried out by considering:

a. To Check for Overall Regression,
   $\alpha = 0.05$

b. To Test for Overall Significance,
   H_O: $\beta 1 = \beta 2 = \beta 3 = \beta 4 = \beta 5 = \beta 6 = \beta 7 = \beta 8 = \beta 9 = \beta 10 = \beta 11 = 0$
   H_1: $\beta j \neq 0$ for at least one j

F_{obs} (26.285) > $F_{critical} = F_{\alpha, p-1=10, n-p=69,} =$ 1.968. The null hypothesis is rejected. Therefore, the model is significant. The significance of the parameters is determined by considering:

- H_o: $\widehat{\beta_J}=0$
- H_1: $\widehat{\beta_J} \neq 0$

  $t_{critical\ (0.025, n-p=69)} = 1.9955$

From the model, $S^2 = 0.7276/69 = 0.010544$

$$t_{obs} = \frac{\beta i\text{^}-\mathbf{0.0}}{\sqrt{(x'x)_{ii}{}^{-1} S^2}}$$

After comparing the t_{obs} to $t_{critical}$, it is found that for X_3, X_6, X_7, X_8, X_9 and X_{10}, I t $_{obs}$ < It $_{critical}$. Therefore, the null hypothesis cannot be rejected. Therefore, X_3, X_6, X_7, X_8, X_9 and X_{10} are removed from the model.

After removing these variables, the 2nd revised model is found as:

$$y = 0.99031 + 0.92765X_1 - 0.020314X_2 - 0.013369X_4 + 0.019786X_5 \quad (6.4)$$

The ANOVA calculation of the 2nd revised model (equation 6.4) is shown in Table 6.7. The 2nd revised model is found as significant since F_{obs} (64.022) > $F_{critical}$= Fα, p-1=10, n-p=69, = 2.4936. After comparing the t_{obs} to $t_{critical}$, it is found that for all parameters $t_{obs} > t_{critical} = 1.9925$. Therefore, they are significant.

Table 6.7: ANOVA of 2nd Revised Model of Terminal IRI

	df	SS	MS	F
Regression	p-1=4	2.707	0.677	64.022
Residual	n-p=75	0.793	0.011	
Total	n-1=79	3.499		

The error is estimated by using the following equation (Montgomery 2009):

$$\sqrt{(\sum(y-\hat{y})^2\ /(n-p)}= \sqrt{(\ SS/(n-p))} \tag{6.5}$$

The covariance and correlation matrix are calculated by using the following equations respectively (Montgomery 2009):

$$\mathrm{Cov}(\hat{\beta}) = (X'X)^{-1}\sigma^2 \tag{6.6}$$

Or, $\mathrm{Cov}(\hat{\beta}) = \left(\underline{X}'\underline{X}\right)^{-1}_{ii} s^2$

$$\text{Correlation, } \rho_{\beta 1,\beta 2} = \frac{\left(\underline{X}'\underline{X}\right)^{-1}_{1,2}}{\sqrt{\left(\underline{X}'\underline{X}\right)^{-1}_{1,1}\left(\underline{X}'\underline{X}\right)^{-1}_{2,2}}} \tag{6.7}$$

The covariance matrix of Terminal IRI model is found as:

	β_0	β_1	β_2	β_4	β_5
β_0	0.007365	-0.004627	0.000047	-0.000127	0.000002
β_1	-0.004627	0.004348	-0.000105	-0.000016	-0.000042
β_2	0.000047	-0.000105	0.000016	0.000000	0.000002
β_4	-0.000127	-0.000016	0.000000	0.000013	-0.000002
β_5	0.000002	-0.000042	0.000002	-0.000002	0.000015

The correlation matrix of the Terminal IRI model is found as:

	β_0	β_1	β_2	β_4	β_5
β_0	1	**-0.8176**	0.1357	**-0.4110**	0.0074
β_1	**-0.8176**	1	**-0.3972**	-0.0678	-0.1624
β_2	0.1357	**-0.39724**	1	-0.0273	0.1234
β_4	**-0.4110**	-0.06785	-0.0273	1	-0.1626
β_5	0.0074	-0.16236	0.1234	-0.1626	1

The parameter β_1 is found as highly correlated to β_0 (0.8176) with high variance, which means the parameters might be less precisely estimated. Also, β_4 is also correlated to β_0. β_1 and β_2 are also correlated to each other. However, the parameters β_0, β_1, β_2 and β_4 might be less precisely estimated.

The confidence level of the parameters is also estimated by using the following equation:

$$\beta_i = \pm t_{\frac{\alpha}{2},n-p}\, s\sqrt{(X'X)ii^{-1}} \qquad (6.8)$$

The t_{obs} values with the confidence level are listed in Table 6.8. The normality of the residuals of the 2nd revised IRI model is also checked. The normal distribution probability plot of the residuals is shown in Figure 6.3.

Table 6.8: Estimated Parameters of 2nd Revised IRI Model

	Coefficient Value	t_{obs}	Lower 95%	Upper 95%
β_0:	0.599031	6.979954601	0.428065592	0.769996472
β_1:	0.927650	14.06778797	0.796287586	1.059011582
β_2:	-0.020314	-5.055516201	-0.028318366	-0.012309248
β_3:	-0.013369	-3.716755965	-0.020534405	-0.006203472
β_4:	0.019786	5.101358357	0.01205924	0.027511963

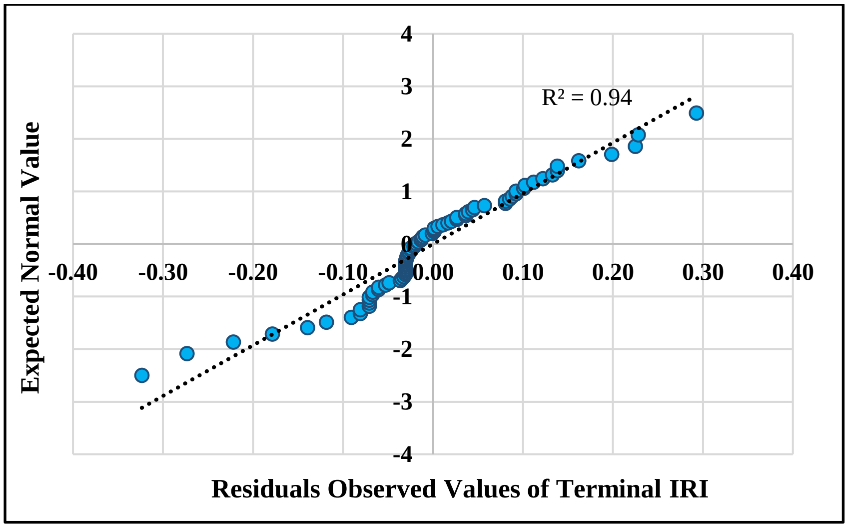


Figure 6.3: Normal Probability Plot of Residuals of Terminal IRI

From Figure 6.3, it is observed that the points are scattered around the straight line (trend line) with some points deviating from the line. Thus, the normality assumption might be satisfied for this data.

The 2nd revised IRI model is further investigated irrespective of additional terms that need to be included in the model. For this purpose, the residuals of the terminal IRI are plotted against the significant variables. Figure 6.4 presents these plots.

From Figure 6.4, it is observed that, although residuals are randomly distributed with predicted IRI from the model, residuals are almost systematically distributed equally on both sides for each variable. This pattern indicates that the model might be missing other interaction terms. Although a significance test with a hypothesis test (t_{obs}) and adjusted R^2 shows the significance and improvement of the 2nd revised model, the IRI model still requires additional interaction terms.

The correlation matrix reveals that the parameter β_0 is highly correlated with β_1 and β_4. β_1 and β_2 are also correlated. From Figure 6.4, it is observed that the interaction term is missing. For that reason, another additional term X1X2 is added into the model to investigate the requirement of the interaction effect. The 3rd revised model of IRI is shown as:

$$y = \beta 0 + \beta 1X_1 + \beta 2X_2 + \beta 4\, X_4 + \beta 5X_5 + \beta 6X1X2 \tag{6.9}$$

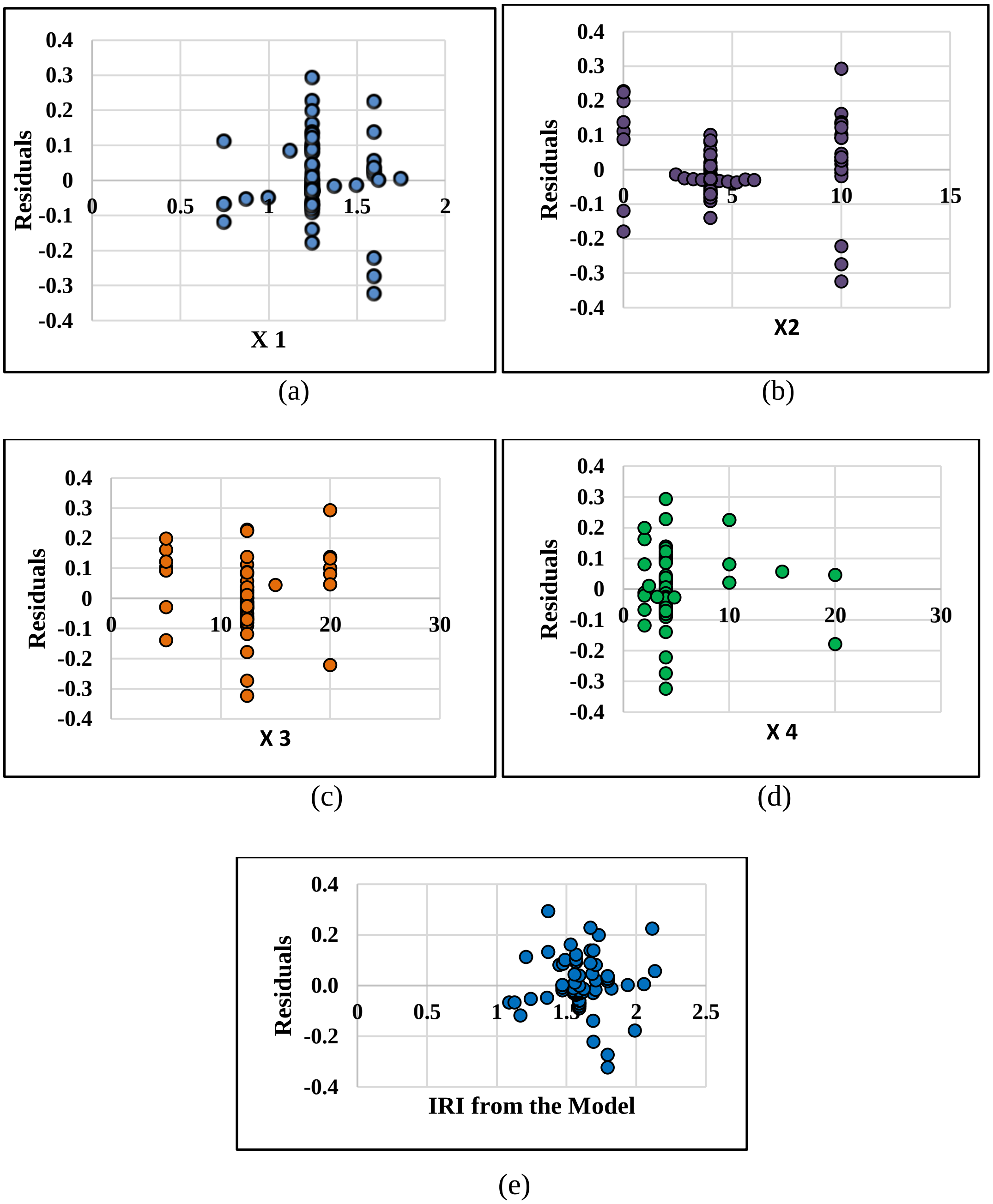


Figure 6.4: Residual of Terminal IRI versus (a) Existing IRI, (b) Existing Initial Permanent Deformation, (c) Effective AC Binder Content, (d) % AC Air Voids, (e) IRI from the Model

Table 6.9: ANOVA of Final IRI model

	df	SS	MS	F
Regression	5	2.771	0.554	56.290
Residual	74	0.728	0.010	
Total	79	3.499		

It is found that the final model of IRI is significant with the parameters as its t_{obs} > $t_{critical}$ =1.99.

Table 6.10: Estimated Parameters of the Final IRI Model

Parameters	Value	t_{obs}	Lower 95%	Upper 95%
β_0	0.32	2.35	0.05	0.59
β_1	1.14	11.00	0.93	1.34
β_2	0.04	1.64	-0.01	0.08
β_4	-0.01	-3.32	-0.02	0.00
β_5	0.02	4.71	0.01	0.03
β_6	-0.04	-2.55	-0.08	-0.01

Therefore, based on the multiple stages of regression analysis, it is found that for IRI, the main effect of the existing initial IRI, existing permanent deformation, AC effective binder content, percentage of air voids and the interaction effect between existing IRI and permanent deformation are significant sensitive inputs.

The main effect is investigated by changing one variable, while keeping the other variables constant. In the IRI model, the investigation of main effect justifies the incorporation of the interaction effect (additional term as an interaction effect of existing IRI and permanent deformation) into the model along with main effects. However, the interaction effects among all other variables are also further investigated from a randomly selected experimental design. In this experimental design, the inputs are changed in combined way to investigate the effect on the predicted distresses accordingly.

With similar steps followed in IRI, the other distresses are investigated too. The experimental design is rearranged with only the inputs that have significant effects, while multiple regression is carried out again for the rearranged sample. In this way, significant sensitive input variables, which have the main effect on distresses, are found. The input variables are ranked based on the higher value of coefficients. Finally, statistically sensitive input variables, which have main effects on the respective distresses, are summarized in Table 6.11.

It is found that permanent deformation in the AC layer is sensitive to the percentage of trucks in the design lane, AC top-layer thickness, TTC type, milled thickness, initial permanent deformation and AC binder penetration grades. For total cracking (reflective and alligator), the sensitivity of the AC top-layer thickness is proven to be statistically significant. The sensitivity of the main effect of effective binder content, AC binder penetration grades and AC air voids are proven to be statistically significant for the AC thermal fracture. Similarly, AC top-down fatigue cracking is found to be significantly sensitive to AC effective binder content, AC air voids, AADTT and AC top-layer thickness. However, no sensitive input variables are found for AC bottom-up fatigue cracking for the experimental sample. Therefore, further investigation is required for AC bottom-up fatigue cracking.

6.4.2 Sensitivity Analysis for Interaction Effects

As discussed, only the sensitive input variables found from the main effect analyses are considered for interaction effects. This experimental design is formed with a total of 58 experimental sets. Of these 58 experimental sets, each output distress is predicted and the effect is observed. A multiple linear regression analysis is carried out for each distress separately, following the similar steps used for indenting the main effects of IRI. In the regression model, only statistically significant variables (which have $t_{observed} > t_{critical}$) are considered. The experimental design is rearranged with only the variables that have significant effects, while multiple regression is carried out again for the rearranged experimental sets. The sensitive combination of input variables is found in this way. The combination of input variables is also ranked based on the higher value of coefficients. Finally, the sensitive interaction of input variables for each distress is summarized in Table 6.12.

Table 6.11: Inputs (Main Effect) as per Sensitivity Ranking of the MEPDG Distresses

Distress	**Inputs as per Sensitivity Ranking**
Terminal IRI	(1) Existing Initial IRI (2) Existing Initial Permanent Deformation (3) AC Air Voids (4) AC Effective Binder Content
Total Permanent Deformation	(1) Initial Permanent Deformation (2) Subgrade Resilient Modulus (3) AADTT (4) AC Top-Layer Thickness (5) Percentage of Trucks in the Design Lane (6) TTC Type (7) Milled Thickness
AC Permanent Deformation	(1) Percentage of Trucks in the Design Lane (2) AC Top-Layer Thickness (3) TTC Type (4) Milled Thickness (5) Initial Permanent Deformation (6) AC Binder Penetration Grade
Total Cracking (Reflective + Alligator)	AC Top-Layer Thickness

Distress	Inputs as per Sensitivity Ranking
AC Thermal Fracture	(1) Effective Binder Content (2) AC Binder Penetration Grade (3) AC Air Voids
AC Top-Down Fatigue Cracking	(1) AC Effective Binder Content (2) AC Air Voids (3) AADTT (4) AC Top-Layer Thickness

Table 6.12: Sensitivity Ranking of Interaction Effect of Inputs from MEPDG Distresses

Distress	Combined Effect of Inputs as per Sensitivity Ranking
Terminal IRI	(1) Existing Initial IRI + Operational Speed (2) Existing Initial IRI + Existing Initial Permanent Deformation
Total Permanent Deformation	(1) Initial Permanent Deformation + Subgrade Resilient Modulus + AADTT (2) Initial Permanent Deformation + AADTT (3) AADTT + Percentage of Trucks in the Design Lane (4) Subgrade Resilient Modulus + AADTT (5) Top-Layer Thickness + Subgrade Resilient Modulus (6) Top-Layer Thickness + AADTT + AC Air Voids
AC Permanent Deformation	(1) AADTT + Percentage of Trucks in the Design Lane (2) Initial IRI + AADTT (3) Initial IRI + Initial Permanent Deformation + Top-Layer Thickness (4) Top-Layer Thickness + Subgrade Resilient Modulus (5) Initial IRI + Initial Permanent Deformation (6) Top-Layer Thickness + AC Air Voids + AADTT (7) Initial Permanent Deformation + Milled Thickness (8) Initial IRI +AC Air Voids (9) Initial IRI + Initial Permanent Deformation + AC Top-Layer Thickness + Milled Thickness (10) Milled Thickness + Subgrade Resilient Modulus
Total Cracking (Reflective + Alligator)	No interaction effect found
AC Thermal Fracture	(1) Effective Binder Content + AADTT (2) Effective Binder Content + AADTT + Percentage of Trucks in the Design Lane (3) Effective Binder Content + Initial Permanent Deformation (4) Effective Binder Content + Initial Permanent Deformation + AC Air Voids + AADTT
AC Top-Down Fatigue Cracking	(1) AC Air Voids + Initial IRI (2) AC Air Voids + Percentage of Trucks in the Design Lane (3) AC Air Voids + Percentage of Trucks in the Design Lane + AADTT (4) Initial IRI + AADTT (5) Initial Permanent Deformation + AC Effective Binder Content + AC Air Voids + AADTT (6) AC Top-Layer Thickness + Subgrade Resilient Modulus (7) Initial Permanent Deformation + AC Top-Layer Thickness + AC Effective Binder Content + AC Air Voids + AADTT

For interaction effects, a number of combinations are found to be sensitive for each distress, except total cracking (reflective and alligator) and AC bottom-up fatigue cracking. Terminal IRI is found to be sensitive to the combination of initial IRI and operational speed. Total permanent deformation is sensitive to the combination of initial permanent deformation-subgrade resilient modulus-AADTT, initial permanent deformation-AADTT, AADTT-percentage of trucks in the design lane, subgrade resilient modulus-AADTT, top-layer thickness–subgrade resilient modulus, top-layer thickness and AADTT-AC air voids. AC permanent deformation is found sensitive to the combination of the AADTT-percentage of trucks in the design lane, initial IRI–AADTT, and initial IRI-initial permanent deformation-top-layer thickness.

The combination of effective binder content-AADTT, effective binder content-AADTT-percentage of trucks in the design lane, effective binder content-initial permanent deformation, and effective binder content-initial permanent deformation-AC air voids-AADTT are proven to be sensitive for AC thermal fracture.

The combination of AC air voids-initial IRI, AC air voids-percentage of trucks in the design lane, AC air voids-percentage of trucks in the design lane-AADTT, initial IRI-AADTT, initial permanent deformation-AC effective binder content-AC air voids-AADTT, AC top-layer thickness-subgrade resilient modulus and initial permanent deformation-AC top-layer thickness-AC effective binder content-AC air voids-AADTT are found to be sensitive for AC top-down fatigue cracking.

6.5 Sensitivity Analysis Summary

This study is mainly focused on identifying the main effects of the independent input variables as well as the interaction effects of the variables on MEPDG distresses. The relative influence of the input variables is needed to identify the high-level accuracy of inputs for precise prediction of the MEPDG distresses.

Since local sensitivity focuses on the local impact of the input variables on the performance of output, this process is carried out to identify the main effect by varying certain inputs, while keeping other inputs constant. Based on a wide range of changes in output distresses with respect to the range of changes in input variables, the input variables with substantial effects on distresses are listed. The relative influences of different input variables are found from the normalized values of the variables in the regression models of each MEPDG distress. To identify the interaction effects, experimental design is formed by taking the random combinations of input variables by changing the multiple variables at a time.

To identify statistically significant sensitive variables and the sensitive combination of variables, multiple linear regression analysis is carried out. Sensitive input variables and their combinations are screened from the statistical significance test and ranked with the higher value of coefficients respectively.

Based on these identified sensitive input variables, the accuracy level of major inputs of specific distresses are to be improved to precisely predict MEPDG-based distresses. The flexibility of ranges of the input variables can also be selected based on this sensitivity analysis for economic pavement design and future research.

The effort to obtain high accuracy levels of only sensitive input variables and their combinations, rather than all input variables, will be more efficient and economical. Laboratory tests of pavement sections can be carried out for the specific properties only. For example, only existing IRI, permanent deformation, AC air voids and AC effective binder content are to be investigated to get Level 1 accuracy for precise predictions of Terminal IRI. Similarly, subgrade resilient modulus is to be investigated for prediction of the permanent deformation. Vehicles' surveys for specific AADTT, percentage of trucks in the design lane and TTC types are to be conducted for precise prediction of the permanent deformation. Since specific sensitive properties are found for respective distresses, it will be more efficient to get higher accuracy levels of these properties through laboratory tests or investigations. Future pavement design will also be efficient and economical based on higher accuracy levels of these specific inputs. Therefore, future prediction of distresses will be improved, which will ensure efficient PMS.

Based on the results found in this chapter, Level 1 accuracy is obtained for sensitive inputs. The MEPDG-based distresses are predicted and analyzed in the next chapter.

CHAPTER 7
APPLICATION OF THE MECHANISTIC-EMPIRICAL APPROACH: PREDICTION, COMPARISON AND VERIFICATION

In a PMS, the performance of pavement structure significantly influences management decisions. That said, accurate prediction and evaluation of performance is an important aspect of M&R strategies. Although the performance of pavement depends on the specific types of materials, traffic load, performance prediction models need to be investigated to ensure precise prediction. This chapter investigates the predicted performance through the M-E approach and compares to field-evaluated performance.

The work of this chapter was presented at the 2017 Transportation Association of Canada (TAC) Conference (Jannat 2017).

7.1 Introduction

As discussed in Chapter 1, the M-E approach is now a state-of-the-art practice for pavement design and enables distress predictions by incorporating the effect of all local factors, including traffic, pavement materials and environmental conditions. Moreover, many recent research works (Schram 2006, Kang 2007, Velasquez 2009, Hall 2010, Hoegh 2010, Walaa 2011, and El-Badawy 2012) validate the efficiency of MEPDG-based pavement design and the precise prediction of distresses. This approach has been adopted by the majority of highway agencies in North America, including many in Canada.

This chapter predicts the distresses by the M-E approach and compares the predicted distresses to the field-evaluated performances. A cluster-based calibration is also conducted based on material types.

7.2 Selected Road Sections

The historical database of the MTO PMS-2 is reviewed to ensure a clear understanding of the available performance data. It is discussed in Chapter 4 that highway sections are homogeneously defined by pavement structure and geographic locations and do not represent homogeneous performance conditions. For this reason, the overall condition is observed over the service life for all road sections. The yearly performance of the selected highway sections is investigated for each performance cycle.

The overall condition is observed in terms of PCI for all road sections. For example, the observed overall condition and service life histogram sections with Superpave mixes are presented in Figure 7.1. This observation confirms how many treatment activities were taken and whether they need to be considered for rehabilitation design during the analysis. The experimental design is formed by considering only the uninterrupted performance cycles.

Finally, a total of 176 performance cycles, which include 1,530 performance years, are investigated for predicting distresses. The experimental design consists of 128 highway sections from 19 highways. These highway sections are screened from a total of 1,800 highway sections with uninterrupted performance cycles for a period exceeding four years. Properties of existing pavement structure and site-specific traffic characteristics available for the investigation are also reviewed.

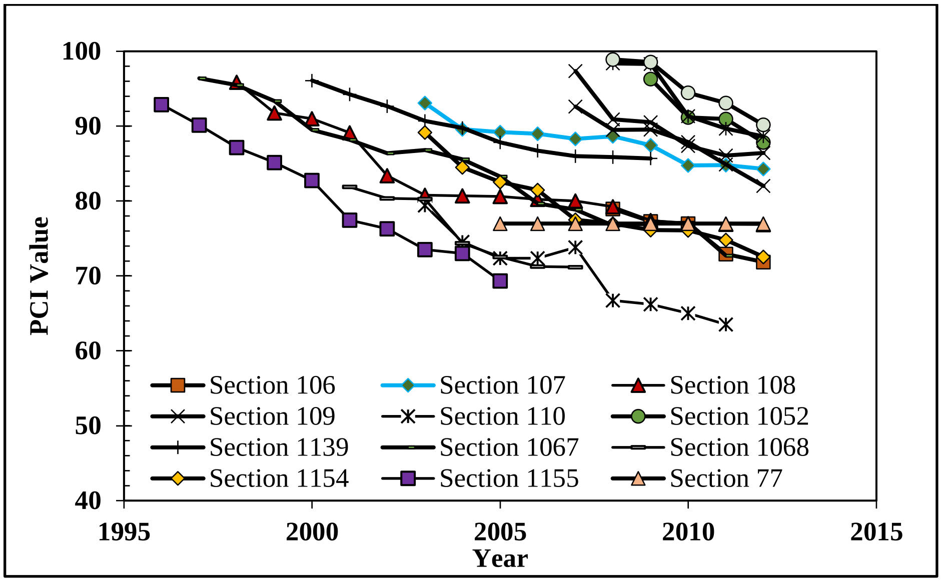
The highway sections are selected both from the Marshall mixes and Superpave mixes. For the sections with Marshall mixes, a total of 113 road sections are selected from the 15 highways. These sections are selected from Southern Ontario (84%) and Northern Ontario (16%) freeways (90%) and arterials (10%). For Superpave, a total of 15 road sections are selected from Southern Ontario, with 11 road sections from the Central region and four road sections from the Western region. These sections are only selected for further investigation if the properties of existing pavement structure, site-specific traffic characteristics were available.

Table 7.1 and 7.2 list the summaries of experimental design within the Marshall mixes and Superpave mixes respectively. Figure 7.2 shows the distribution of the selected road sections.

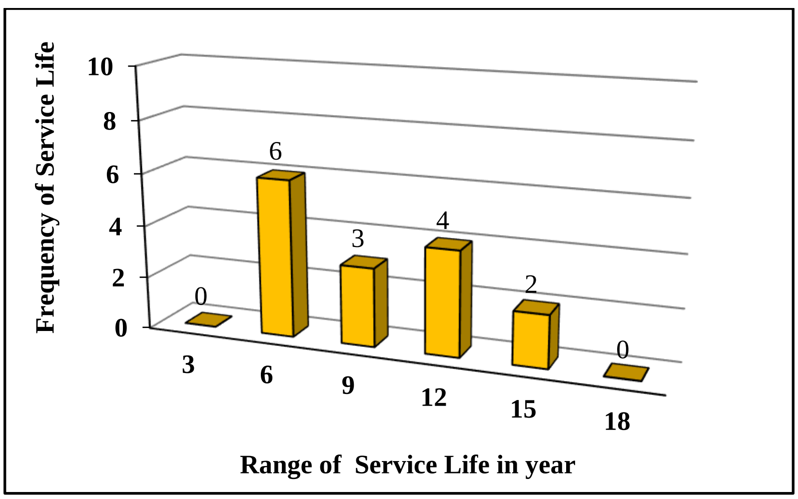
7.3 Evaluation of Performance Predictions Using M-E Approach

This chapter investigates the performance predictions through the M-E approach and compares those predications to the field-evaluated performance.

This study is carried out in three steps. The M-E approach is followed in the first step to predict the major distresses. These distresses are predicted by using the AASHTOWare Pavement-ME software. For precise and efficient prediction, Level 1 accuracy is obtained for all possible inputs identified as sensitive in the previous chapter. In the second step, the predicted distresses are compared to the field-evaluated performance. In the third step, the prediction models are calibrated and validated. The literature review justifies the requirement of local calibration for the prediction models (NCHRP 2004, AASHTO 2008, AASHTO 2010, Schram 2006, Velasquez 2009, 2009 Hall 2010 and Hoegh 2010). The purpose of local calibration is to reduce potential biases and the variation of performance predictions by the globally calibrated prediction models. This research calibrated the prediction models based on the cluster-based regression for surface layer material types. The surface layer material-based cluster is used in this study because one of the research objectives is to incorporate the effect of surface materials into the prediction models of the overall condition index. For this reason, this study considers the cluster analysis based on surface materials and does not calculate the local calibration coefficients in the transfer models.Figure 7.3 presents the steps of the methodology that are followed in this study.



(a)



(b)

Figure 7.1: (a) Field Observed Overall Condition of Pavement, and (b) Service Life Distribution of the Road Sections with Superpave Mixes

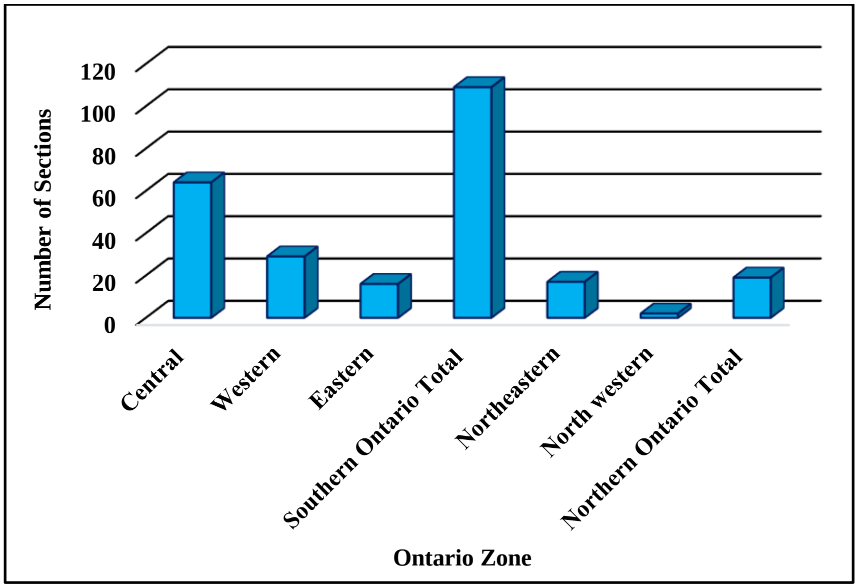


Figure 7.2: Pavement Section Selected for Experimental Design

Table 7.1: Selected Pavement Sections with Marshall Mix for Experimental Design

Source of Highway Sections	**No. of Pavement Sections**
Southern Ontario Total	95
Central Region	53
Western Region	25
Eastern Region	17
Northern Ontario Total	19
Northwestern Region	2
Northeastern Region	17
Freeways	102
Arterials	11
4OO-Series Highways	68
Marshall Mix Total	**113**

Table 7.2: Selected Superpave Sections for Experimental Design

Region	Highway	Section Name	Length (km)	No. of Lanes
Central	6	106	5.90	4
	6	107	8.17	4
	6	108	4.48	2
	6	109	2.94	2
	6	110	1.37	2
	401	1052	4.12	5
	401	1139	4.12	3
	401	1067	9.23	3
	401	1068	12.66	3
	401	1154	9.23	3
	401	1155	12.66	3
Sub-Total	**2**	**11**	**74.89**	
Western	3	77	12.20	2
	3	78	1.20	2
	7	197	7.32	2
	7	206	7.32	2
Sub-Total	**2**	**4**	**28.04**	
Total	**4**	**15**	**102.94**	

7.3.1 Prediction of MEPDG-based Distresses

At first, the three major inputs of the AASHTOWare Pavement-ME software are collected for the selected highway sections. It is discussed in Chapter 3 that the input data required for the AASHTOWare Pavement-ME analysis are mainly traffic, climate, pavement structure and material properties.

Traffic Data

As discussed in Chapter 3, in AASHTOWare Pavement-ME traffic inputs, include traffic volume adjustment factors, axle-load distribution factors and general traffic inputs.

It is observed that on road sections with Marshall mixes, the AADT in year one varies from 5,000 to 138,000, whereas with Superpave mixes, it varies from 8,000 to 171,000. It is observed that for the sections with Marshall mixes, AADTT varies from 400 to 36,000. It is observed that the AADT in year one for the sections with the Superpave mixes vary from 5,000 to 25,000 with a compound growth factor that varies from 2.07 to 2.71. The percentage of truck traffic varies from 5.53% to 20% among the highway sections. Figure 7.4 presents distribution patterns of the AADT, AADTT and traffic growth factors of road sections.

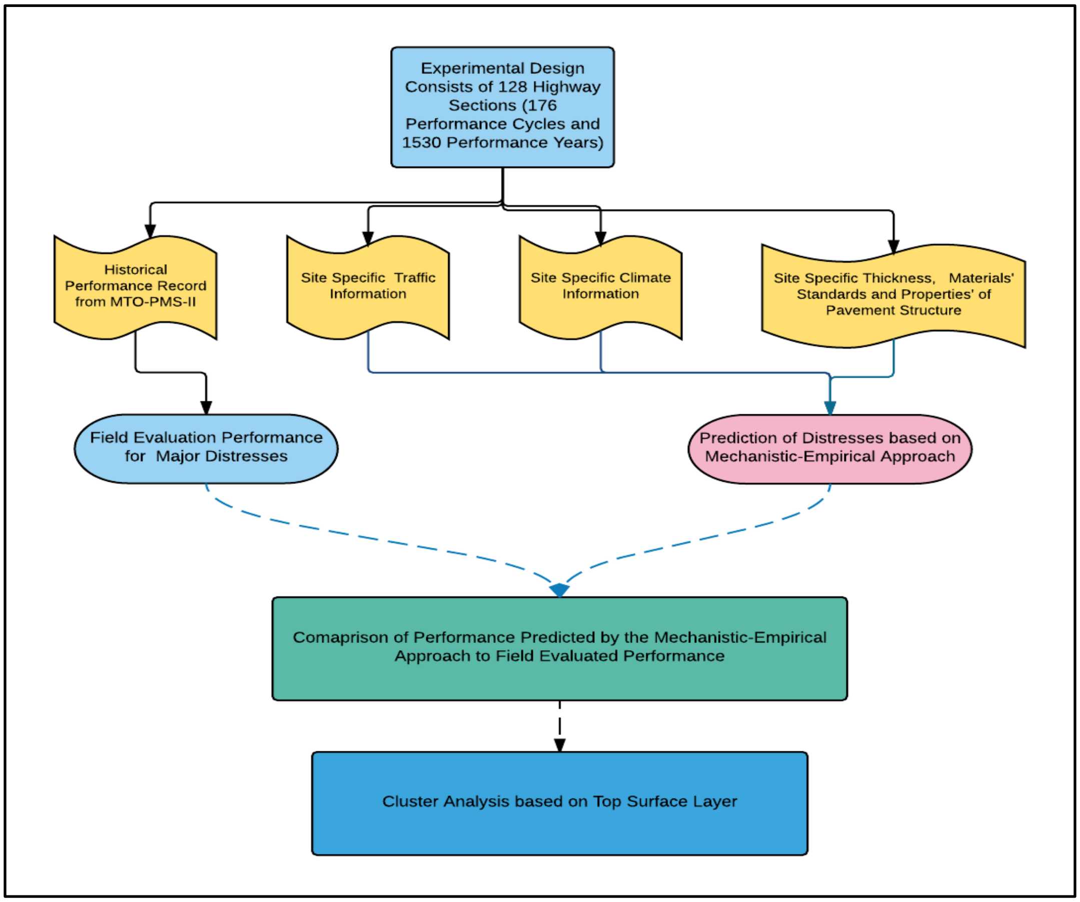


Figure 7.3: Steps in Evaluation of Performance Prediction Using M-E Approach

Material Properties

As discussed in the previous section, the highway sections with Marshall mixes and Superpave mixes are considered for empirical investigation. The highway sections consisting of similar material properties of the existing pavement structure are taken into consideration so that performance can be compared in a consistent way. Moreover, for accurate prediction of the distresses, a higher level of accuracy is obtained for inputs that are identified as sensitive in the previous chapter. For this reason, materials properties with Level 1 accuracy are collected in the study.

From the PMS-2 database, the layers of the existing pavement structure are investigated. Since AASHTOWare Pavement-ME software is able to only analyse the overlay design of the M&R activities, this study will only consider the overlay design to be consistent. The pavement structure of the selected highway sections with Marshall mixes is mainly found as an overlay with dense friction course (DFC) and different types of hot laid (HL) asphalt surface layers such as HL-1, HL-3, HL-3M, HL-4 and HL-8. The properties and use of different HL layers available on Ontario highways are summarized in Table 7.3. The gradation of mix design criteria of these layers recommended by the MTO (MTO 2010) are listed in Table 7.4.

In this study, Superpave SP12.5 FC2 with the performance grade (PG) 70-28, PG 58-28 and SP19.0 with PG 64-28 are considered for this investigation. The latest edition of the material specifications (OPSS 1150 and 1151) is followed in this study to predict the MEPDG-based distresses (MTO 2007, MTO 2010). The Superpave mix designs developed based on the requirements of OPSS specifications are shown in Table 7.5.

However, considering all traffic data, climate conditions and material properties, the distresses are predicted based on the M-E approach for 176 performance cycles.

7.3.2 Comparison to Field-Evaluated Performance

After predicting the distresses, the predicted distresses are compared to the field-observed distresses. The predicted failure is also investigated and compared to Ontario's standard threshold value of failure for the specific distresses. It is found that some road sections exceed the threshold value of failure within the service life. These failure road sections are further investigated and compared to the field-evaluated scenario. Table 7.6 lists the failure sections in both the predicted and field-evaluated cases.

Although the performance of pavement depends on the types of materials, traffic load and other factors may have a significant impact as well. For this reason, traffic patterns, service life and types of failure are investigated to identify the influential factors affecting failure. For example, a summary of AADT, traffic growth factors, service life and corresponding failure types of road sections with Superpave mixes are presented in Table 7.7. It is observed from Table 7.7 that for most of road sections predicted distresses have failure whereas failure was not found in case of field evaluation. This indicates requirement of local calibration of prediction models.

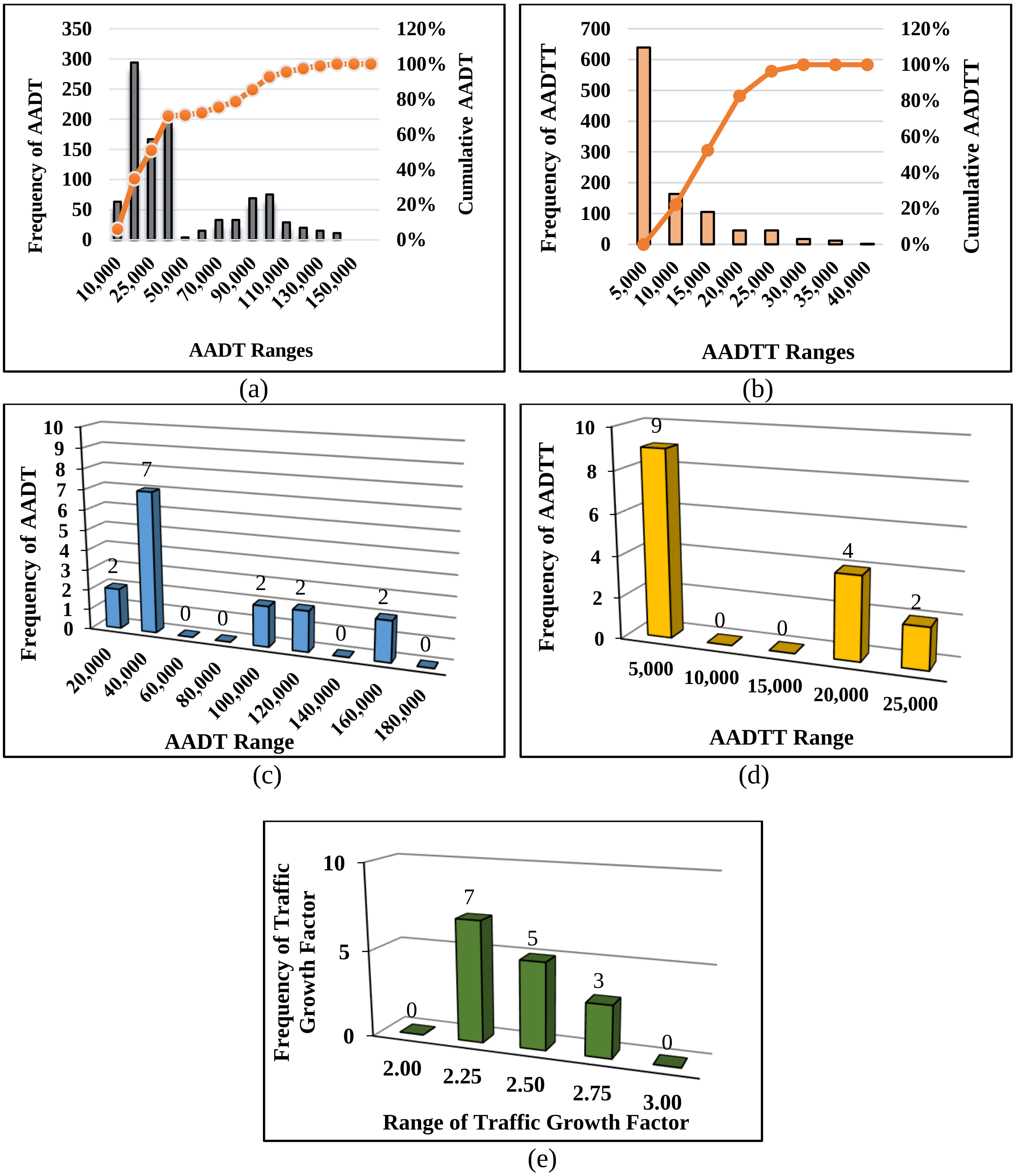


Figure 7.4: Distribution Pattern of (a) AADT (Marshall Mixes), (b) AADTT (Marshall Mixes) and (c) AADT (Superpave Mixes), (d) AADTT (Superpave Mixes) (e) Traffic Growth Factor (Superpave Mixes)

Table 7.3: Hot Mix Surface Layers and Properties

Hot Mix Type	Abbreviation	Summary of Hot Mix Use and Properties
Dense Friction Course	DFC	A dense-graded surface course mix with high frictional resistance for high volume roads. Aggregates have an identical gradation to HL 1 aggregates with a maximum aggregate size of 16mm. Premium 100% crushed aggregates are used for fine and coarse aggregates from the same source.
Hot Laid 1	HL-1	A dense-graded surface course mix with a premium quality coarse aggregate. It is used on high volume roads and has a maximum aggregate size of 16mm. Coarse aggregates are 100% crushed material.
Hot Laid 2	HL-2	A sand mix used primarily as a levelling course on existing pavements or a surface course on low-speed traffic areas requiring a thin overlay. It is also used to fill wide cracks and has 100% of the aggregate passing the 9.5mm sieve size.
Hot Laid 3	HL-3	A dense-graded surface course mix for intermediate volume roads with a maximum aggregate size of 16mm.
Hot Laid 3 High Stability	HL-3HS	A dense-graded padding and levelling mix of high stability. The coarse aggregate conforms to the physical requirements of HL 3 with a maximum aggregate size of 16mm. The fine aggregate conforms to the same physical requirements as HDBC. Coarse and fine aggregates are 100% crushed material.
Hot Laid 3 Fine	HL-3F	A fine-graded mix used as a surface course where hand work is necessary for placement. It is also used on low volume roads, driveways, boulevards, etc. The maximum aggregate size is 16mm.
Hot Laid 4	HL-4	A dense-graded mix used as a surface or binder course on low volume roads. The maximum aggregate size is 19mm.
Hot Laid 4 Fine	HL-4F	A fine graded mix used as a surface course where hand work is necessary for placement. It is also used on low volume roads, driveways, boulevards, etc. The maximum aggregate size is 19mm.
Hot Laid 8	HL-8	A coarse-graded binder course mix. The maximum aggregate size is 26.5mm.
Medium Duty Binder Course	MDBC	A binder course mix intended for use in locations where rutting and deformation is likely to occur due to frequent heavy traffic loading. A minimum of 80% of the coarse aggregates must have two crushed faces and the maximum aggregate size is 26.5mm.
Heavy Duty Binder Course	HDBC HL-8HS	A high stability binder mix designed to provide superior resistance to rutting. Both fine and coarse aggregates are 100% crushed material. The maximum aggregate size is 26.5 mm.

Table 7.4: Mix Design Criteria of Hot Mix Surface Layers

Mix Types	Percentage Passing by Dry Mass of Aggregates											
	Sieves											
	mm								µm			
	26.5	**19.0**	**16.0**	**13.2**	**9.5**	**4.75**	**2.36**	**1.18**	**600**	**300**	**150**	**75**
DFC HL-1			100	98-100	75-90	(Note1)	36-64	25-58	16-45	7-26	3-10	0.5
HL-2					100	85-100	70-90	50-75	30-55	15-55	5-16	3-8
HL-3 HL - 3HS			100	98-100	75-90	50-60	36-60	25-58	16-45	7-26	3-10	0-5
HL-3F			100	98-100	85-94	65-75	52-75	36-72	23-56	10-32	3-12	0-6
HL-4		100	98-100	83-95	62-82	45-60	27-60	16-60	8-47	4-27	1-10	0-6
HL-4F		100	98-100	90-98	80-92	65-80	52-80	36-72	21-56	10-32	3-12	0-6
HL-8 MDBC	100	94-100	77-95	65-90	48-78	30-50	21-50	12-49	6-38	3-22	1-9	0-6
HDBC	100	94-100	77-95	65-90	48-78	(Note 2)	21-54	12-49	6-38	3-22	1-9	0-6

Notes:

1. HL 1 mix for use on facilities with a posted speed of less than 80 km/h shall contain a maximum of 60% by volume of the total aggregates passing the 4.75 mm sieve.
   HL 1 mix for use on facilities with a posted speed of 80 km/h or greater shall contain a maximum of 50% by volume of the total aggregates passing the 4.75 mm sieve.
   DFC mix shall contain from 50-55% by volume of the total aggregates passing the 4.75 mm sieve.
2. HDBC shall contain from 35-52% by volume of the total aggregates passing the 4.75 mm sieve.

Table 7.5: Superpave Mix Design Properties for Ontario Highways

Property	Sieve Size (mm)	OPSS[10] Requirement	Superpave 12.5 FC2 PG 58-28	Superpave 12.5 FC2 PG 70-28	Superpave 19.0 PG 64-28
Gradation (% Passing)	19.0	90 – 100	-	-	95.9
	16.0	-	99.9	100	88.4
	12.5	90 – 100	94.8	98.2	79.5
	9.5	45 – 90	79.6	83.4	70.8
	6.7	-	64.6	65.2	60.3
	4.75	45 – 55	55.0	56.2	53.2
	2.36	28 – 58	42.8	48.0	41.1
	1.18	-	32.6	36.9	29.3
	0.600	-	23.8	27.9	22.1
	0.300	-	13.2	17.5	15.6
	0.150	-	5.9	10.2	8.20
	0.075	2 – 10	3.0	5.8	4.20
N_{des} (% G_{mm})		96.0	96	96	96
N_{ini} (% G_{mm})		≤ 89.0	89	89	88.5
N_{max} (% G_{mm})		≤ 98.0	97	97.8	97.3
Air Voids (%) at N_{des}		4.0	4.0	3.9	4.0
Voids in Mineral Aggregate, VMA (% minimum)		14.0	14.3	14.1	13.0
Voids Filled with Asphalt, VFA (%)		65 – 75	72.2	72.1	72.0
Dust Proportion (DP)		0.6 – 1.2	0.7	1.2	1.0
Asphalt Film Thickness (μm)		-	9.0	6.8	7.9
Asphalt Cement Content (%)		-	5.0	4.9	4.65
Unit Weight (kg/m^3)		-	2520		2460

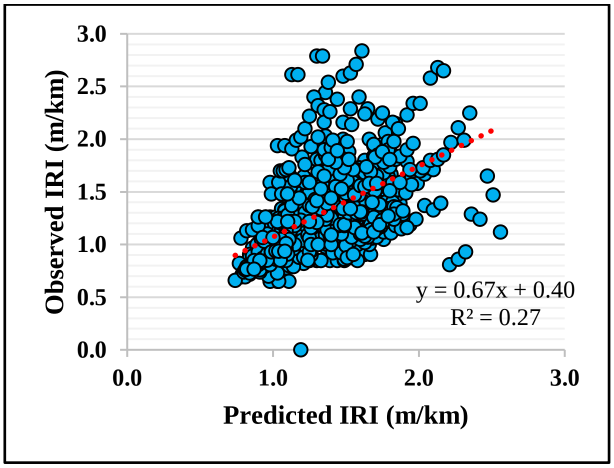
[10] OPSS is Ontario Provincial Standard Specification. N_{odes}, N_{ini}, N_{max} are number of gyrations at different compaction levels (design, initial, and maximum), and G_{mm} is theoretical maximum specific gravity.

Table 7.6: Summary of Failure Sections with Average Value of Distresses

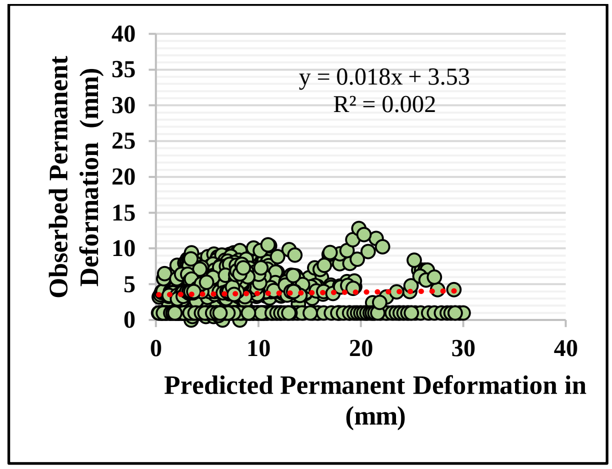
No. of Section Failures	Total Cracking (Reflective + Alligator) (%)	Terminal IRI (m/km)	Permanent Deformation Total (mm)	AC Thermal Cracking: Prediction (m/km) Field Evaluation (%)	AC Bottom-Up Fatigue Cracking (%)	AC Top-Down Fatigue Cracking: Prediction (m/km) Field Evaluation (%)	Permanent Deformation AC Only (mm)
Sections with Marshall Mixes							
No. of Section Failures in Predicted Distresses	0	22	23	13	1	9	15
% of Predicted Failure Sections	0.00%	15.38%	16.08%	9.09%	0.70%	6.29%	10.49%
Average Predicted Value	13.24	1.63	16.42	42.84	0.81	95.05	10.00
No. of Failures in Observed Distresses	N/A	21	0	0	0	0	N/A
% of Observed Failure Sections	N/A	14.69%	0.00%	0.00%	0.00%	0.00%	N/A
Average Field Evaluation Value	N/A	1.51	5.43	12.00	0.48	14.00	N/A
Sections with Superpave Mixes							
No. of Failure Sections in Predicted Distresses	14	8	6	0	0	0	8
% of Predicted Failure Sections of Total	93.33%	53.33%	40.00%	0.00%	0.00%	0.00%	53.33%
Average Predicted Value	23.67	2.02	18.68	5.15	1.45	139.63	8.29
No. of Failure Sections in Field Evaluation	N/A	1	1	0	3	0	N/A
% Field-Evaluated Failure Sections of Total	N/A	6.67%	6.67%	0.00%	20.00%	0.00%	N/A
Average Field Evaluation Value	N/A	1.36	6.18	0	12.92	2	N/A

Table 7.7: Summary of Failure Types, Traffic and Service Life for Superpave Sections

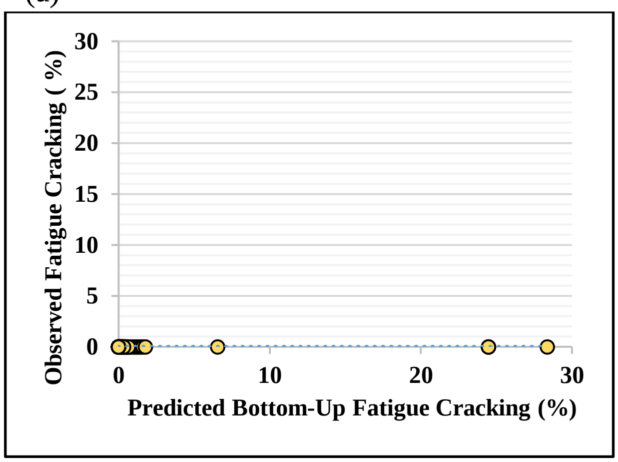
Section Name	AADT Year One	AADTT in Year One	% of Trucks	Traffic Growth Factor	Service Life (Years)	Failure Type in Prediction at End of Service Life	Failure Type in Field Evaluation at End of Service Life
106	31,400	2,800	8.92	2.14	5	No Failure Except Reflective Cracking	Failure in Bottom-Up Fatigue Cracking
107	26,800	2,988	11.15	2.07	10	Failure in IRI	Failure in Bottom-Up Fatigue Cracking
108	24,900	3,100	12.45	2.11	14	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	No Failure
109	24,900	3,536	14.2	2.11	6	No Failure Except Reflective Cracking	
110	23,400	4,156	17.76	2.11	9	Failure in IRI and Permanent Deformation Total	Failure in Bottom-Up Fatigue Cracking and IRI
1052	157,700	17,656	11.2	2.71	4	Failure in Permanent Deformation AC	No Failure
1139	157,700	17,656	11.2	2.71	10	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	No Failure
1067	110,100	22,020	20	2.42	15	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	No Failure
1068	97,400	19,342	19.86	2.28	7	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	No Failure
1154	110,100	22,020	20	2.42	10	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	No Failure
1155	97,400	19,342	19.86	2.28	11	Failure in IRI, Permanent Deformation Total and Permanent Deformation AC	Failure in Total Permanent Deformation
77	9,400	520	5.53	2.46	8	No Failure Except in Reflective Cracking	No Failure
78	10,100	600	5.94	2.66	6	No Failure Except in Reflective Cracking	No Failure
197	21,300	2,400	11.27	2.11	5	No Failure Except in Reflective Cracking	No Failure
206	21,300	2,400	11.27	2.11	5	No Failure Except in Reflective Cracking	No Failure



(a)



(b)



(c)

Figure 7.5: Comparison of Predicted with Observed Distresses: (a) IRI, (b) Permanent Deformation, and (c) Bottom-up (alligator) Fatigue Cracking

Field-evaluated distress is investigated for 176 performance cycles. It is noted that for Terminal IRI, permanent deformation total and AC bottom-up fatigue cracking can be compared directly to the respective predicted values as they are measured with the similar unit in both cases. However, AC thermal fracture (unit = m/km in MEPDG approach and % = field evaluation) and top-down fatigue cracking (unit = m/km in MEPDG approach and % = field evaluation) could not be compared as they have a different unit.

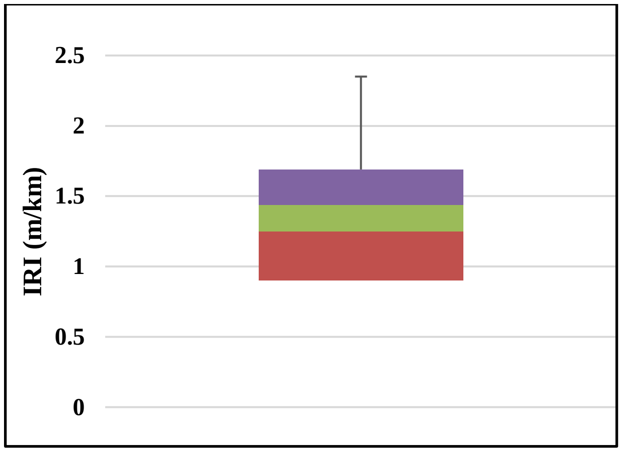
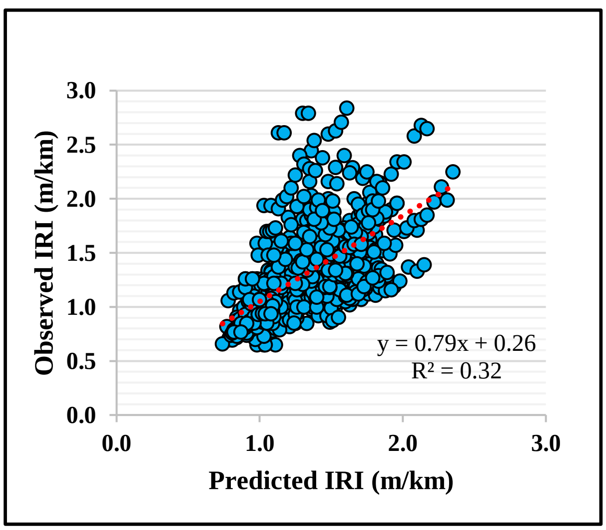
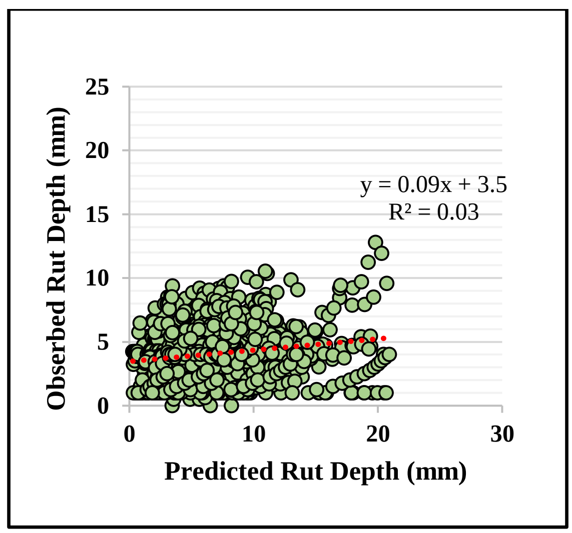


Figure 7.6: Box plot for IRI values





(a) (b)

Figure 7.7: Comparison of Predicted with Observed Distresses: (a) IRI, and (b) Permanent Deformation after Removing Outliers

The predicted and field-observed values for each type of cracking and IRI are compared to capture the trends in both approaches. The predicted distresses are compared against observed distresses to reduce bias and standard error between the predicted and measured values. Initially, the predicted values versus the observed values for IRI, permanent deformation and AC bottom-up fatigue cracking are plotted in the ‘scatter plot’, since measured units are similar to those of the predicted distresses. Figure 7.5 presented the comparison of the predicted values versus the observed values for IRI, permanent deformation and AC bottom-up fatigue cracking respectively.

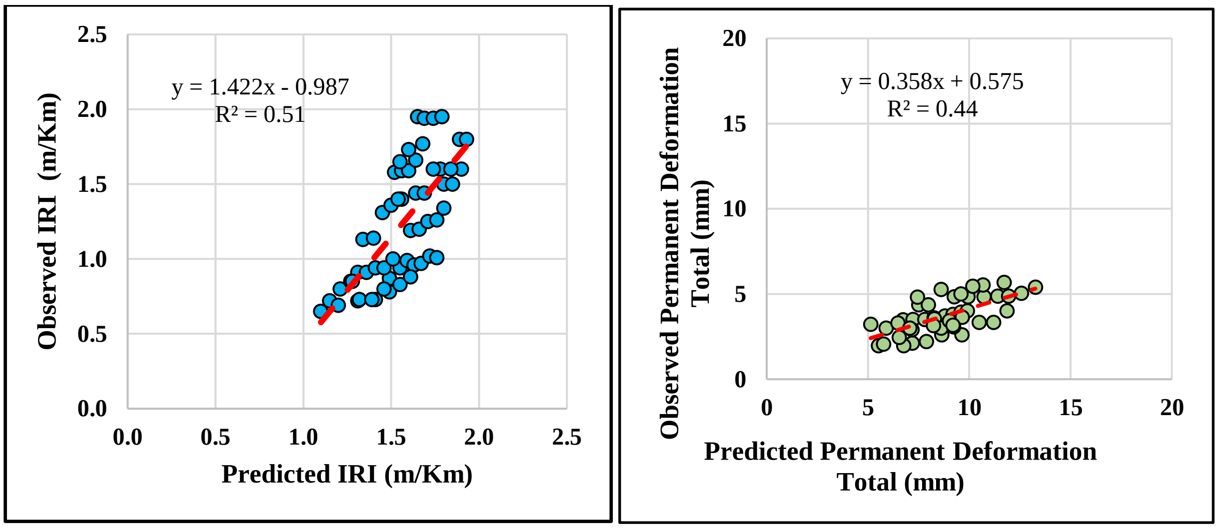


Figure 7.8: Comparison of Predicted with Observed Distresses: (a) IRI, and (b) Permanent Deformation for Sections with SuperPave Mixes

From Figure 7.5, it is observed that for some sections, IRI predicted values are higher than the field-observed values. However, the predicted permanent deformation is over-predicted compared to the field-observed permanent deformation. Bottom-up fatigue cracking cannot be compared due to the lower value in prediction. After comparing the distresses, outliers are identified using a statistical tool, referred to as a ‘box plot’. Figure 7.6 shows the ‘box plot’ for IRI values. Based on the ‘box plot’, it is observed that 2.35m/km to 3.01 m/km are upper outliers. However, no range for lower outliers was found for these data sets. The outliers are removed from permanent deformation and bottom-up fatigue cracking as well by using the ‘box plot’. After removing the outliers, the comparison of predicted values versus observed values are presented in Figure 7.7.

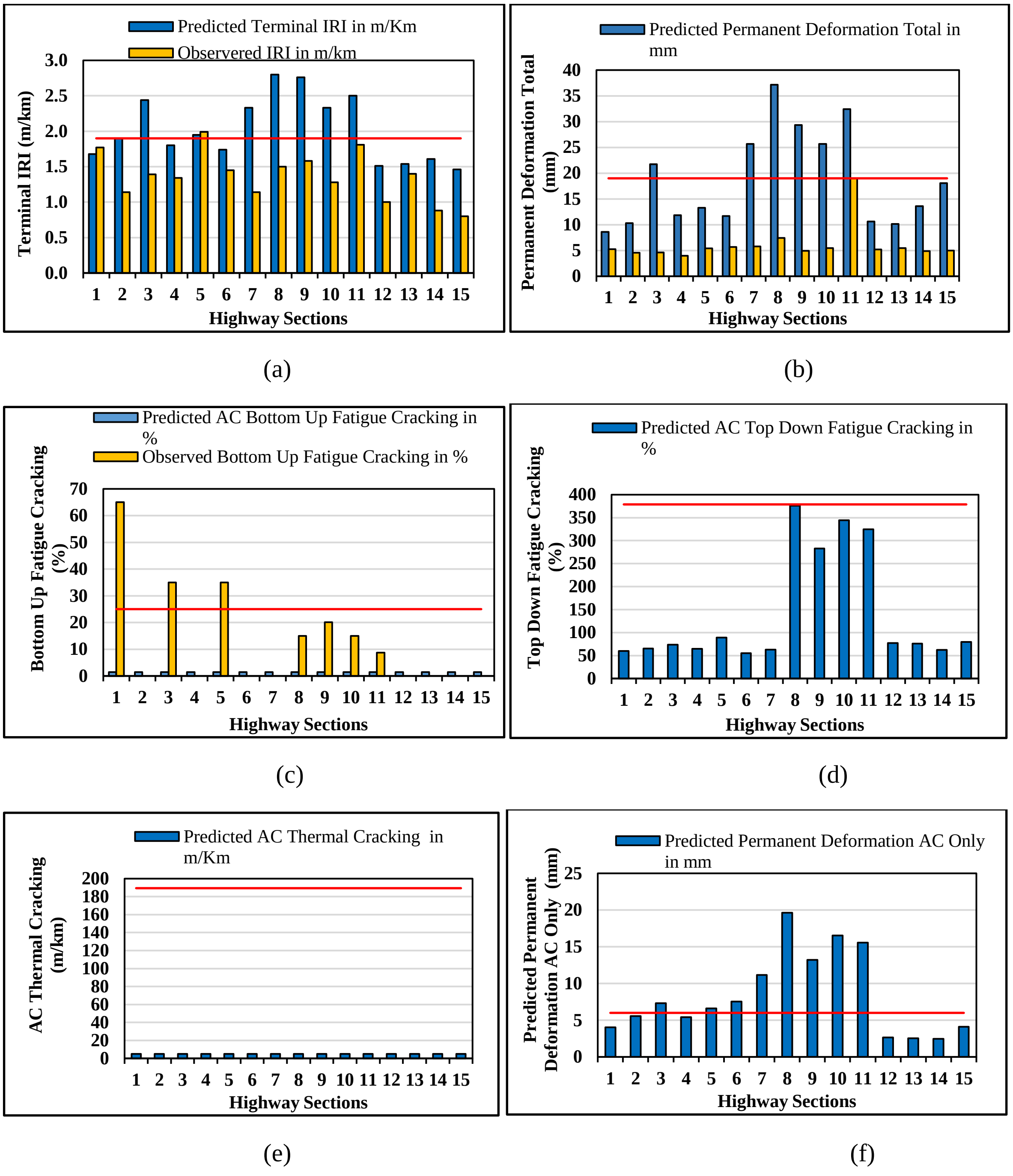


Figure 7.9: Comparison of Predicted Versus Field-Observed (a) Terminal IRI, (b) Permanent Deformation Total, (c) Bottom-up Fatigue Cracking, (d) Top-down Fatigue Cracking, (e) Thermal Cracking, and (f) Permanent Deformation AC for Sections with Superpave Mixes

Table 7.8: Cluster Analysis Summary for IRI

Cluster Group	Before Clustering			
	Predicted Value	**No of Observations**	**Standard Error**	**R^2 value**
Before Clustering with Outliers	Calibrated Predicted IRI= 0.763 Predicted IRI+ 0.3985	1,084	0.357	0.267
Before Clustering after Removing Outliers	Calibrated Predicted IRI = 0.795x Predicted IRI + 0.257	1,028	0.323	0.324
Cluster Name	**Cluster Analysis**			
	Predicted Value	**No of Observations**	**Standard Error**	**R^2 value**
DFC	Calibrated Predicted IRI = 0.762x Predicted IRI + 0.258	382	**0.28**	**0.38**
HL1	Calibrated Predicted IRI = 0.489x Predicted IRI + 0.757	329	**0.21**	**0.39**
HL3	Calibrated Predicted IRI = 0.92x Predicted IRI + 0.109	110	**0.23**	**0.47**
HL3M	Calibrated Predicted IRI = 0.263x Predicted IRI + 0.938	74	**0.23**	0.21
HL4	Calibrated Predicted IRI = 0.126x Predicted IRI +1.044	60	**0.19**	**0.34**
HL8	Calibrated Predicted IRI = 0.744x Predicted IRI + 0.326	12	**0.05**	**0.38**
Superpave	Calibrated Predicted IRI = 1.42 x Predicted IRI -0.987	59	**0.28**	**0.51**
Total		**1,026**		

To improve the goodness of fit further, a clustering regression analysis is conducted. Since the material properties have a substantial effect on the prediction of distresses, which were discussed in the previous chapter, they are further compared to field-observed distresses based on the material properties. All types of AC layers in Marshall mixes are taken into consideration for further investigation. For example, Figure 7.8 presents the comparison of IRI after permanent deformation for sections with Superpave mixes after cluster analysis. Figure 7.8 reveals that the observation points are now distributed close to a 45^{o} line with improved R^2 for both cases of IRI and permanent deformation. For all other surface layers, this comparison is carried out accordingly. Following this comparison and clustering analysis, the results of the initial cluster analysis are summarized for IRI and permanent deformation in Table 7.8 and 7.9 respectively.

For further understanding, all the distresses are compared to the field-observed distresses along with the threshold value of failure for each type of surface layer. For example, Figure 7.9 illustrates this comparison of predicted and field-observed values for each type of cracking and IRI. For comparison, the given distress is also allied to a threshold value of failure.

Table 7.9: Summary of Cluster Analysis for Permanent Deformation

Cluster Group	**Before Clustering**			
	Predicted Value	**No of Observations**	**Standard Error**	**R^2 value**
Before Clustering with Outliers	Calibrated Predicted Permanent Deformation = 0.763 Predicted Permanent Deformation + 0.399	1,084	5.68	0.0018
Before Clustering After Removing Outliers	Calibrated Predicted Permanent Deformation = 0.777x Predicted Permanent Deformation + 0.276	1,052	4.2	0.0315
Cluster Name	**Cluster Analysis**			
	Predicted Value	**No. of Observations**	**Standard Error**	**R^2 value**
DFC	Calibrated Predicted Permanent Deformation = 0.243x Predicted Permanent Deformation + 3.033	330	**1.21**	**0.20**
HL1	Calibrated Predicted Permanent Deformation = 0.227x Predicted Permanent Deformation + 3.64	329	**1.98**	**0.12**
HL3	Calibrated Predicted Permanent Deformation = 0.223x Predicted Permanent Deformation + 3.48	101	**1.54**	**0.13**
HL3M	Calibrated Predicted Permanent Deformation = 0.362x Predicted Permanent Deformation + 2.55	60	**1.51**	**0.33**
HL4	Calibrated Predicted Permanent Deformation = 0.366x Predicted Permanent Deformation + 1.8	44	**2.21**	**0.16**
HL8	Calibrated Predicted Permanent Deformation = 0.677x Predicted Permanent Deformation + 0.939	12	**0.85**	**0.61**
Superpave	Calibrated Predicted Permanent Deformation = 0.358x Predicted Permanent Deformation + 0.575	46	**0.79**	**0.44**
Total		**845**		

After the cluster analysis, improved goodness of fit (improved standard of error and R^2) is observed for each model of IRI. However, lower R^2 is found for the IRI model of road sections with HL-3M. However, the improved goodness of fit (lower standard of error and higher R^2) is found for all calibrated models of permanent deformation compared to previous models after removing the outliers.

Although the existing pavement structure is similar, the field performance varies differently over the service life among the road sections. From Figure 7.1, it is evident that at the end of the service life, the condition of pavement varies with a PCI value from 90 to 65. The service life also varies from four to 15 years among these road sections.

In Table 7.6, MEPDG-based distresses show over-prediction of failure than in field-observed values for road sections with Marshall mixes and Superpave mixes. For example, in road sections with Superpave mixes, MEPDG-based predictions show failure in IRI for eight highway sections (53.33% of 15 highway sections), while the field-observed case only shows one failure. Similarly, failure in predicted permanent deformation (total) is found in six highway sections (40% of the 15 highway sections), while the field-observed case only shows one failure (6.67% of the 15 highway sections). For Marshall mixes, in the observed scenario, no failure is found in permanent deformation and thermal cracking. However, in the case of the MEPDG prediction, 23 failures are found in permanent deformation and 13 failures in thermal cracking. In the case of Superpave mixes, no failures were found for thermal cracking and top-down fatigue cracking.

The comparison of bottom-up fatigue cracking portrays an entirely different picture. For bottom-up fatigue cracking, field-observed values show three failures in road sections with Superpave mixes (20% of the 15 highway sections) and one failure in the road sections with Marshall mixes. In the M-E approach, no failures are found. In the case of Superpave mixes, predicted values of total cracking (reflective and alligator) and AC permanent deformation confirm failure in 14 road sections (93.33% of total highway sections) and eight road sections (53.33% of total highway sections). For road sections with Marshall mixes, predicted AC permanent deformation confirms failure in 15 road sections.

In the end of service life, the predicted failures are compared for all road sections. Failure cases for road sections with Superpave mixes are investigated and presented in Table 7.7. From Table 7.7, it is observed that road sections (section 108 and 1067) with a higher service life, exceeding 14 years, forecast predicted failure in IRI, total permanent deformation and AC permanent deformation. Despite low AADT (AADT 24,900), failure is found in section 108. Failure in predicted permanent deformation is found due to high levels of traffic, where AADT is more than 97,000 and AADTT is more than 17,000 in section 1052, 1139, 1067, 1068, 1154 and 1155, regardless of the length of service life. The service life of these sections outlined above vary from four to 15 years.

From Figure 7.5, it is observed that for some sections, IRI predicted values are higher than field-observed values. However, the predicted permanent deformation is found to be over-predicted compared to field-observed permanent deformation. Bottom-up fatigue cracking cannot be compared due to the lower values in the predictions.

After removing outliers, improved R^2 is found in both cases of IRI and permanent deformation, which is presented in Figure 7.7. After the cluster analysis, 'goodness of fit' is further improved. Figure 7.8 shows improved R^2 for both IRI and permanent deformation of road sections with Superpave mixes.

All other distresses are also compared for each type of material. Figure 7.9 portrays the comparison of predicted values versus observed distress values for road sections with Superpave mixes. From Figure 7.9, it is observed that predicted IRI shows slightly higher values than in field-evaluated values. Similarly, total permanent deformation shows higher values than field-evaluated values. The reverse scenario is found in bottom-up fatigue cracking. Bottom-up fatigue cracking is found as under-predicted, with failure sections found in the field evaluation. However, total cracking (reflective and alligator) and AC permanent deformation cannot be compared to field-observed values, since they are not evaluated in the field separately. Nevertheless, total permanent deformation is evaluated over the whole pavement structure, which includes AC permanent deformation.

To improve the goodness of fit further, a clustering regression analysis is carried out that considers the properties of the surface layer. Table 7.8 and 7.9 present the cluster analysis of IRI and permanent deformation respectively.

From Table 7.8, it is found that after removing outliers, R^2 is improved and a lower standard of error is found. However, after clustering, improved R^2 is found for all of AC layer types, except HL3M.

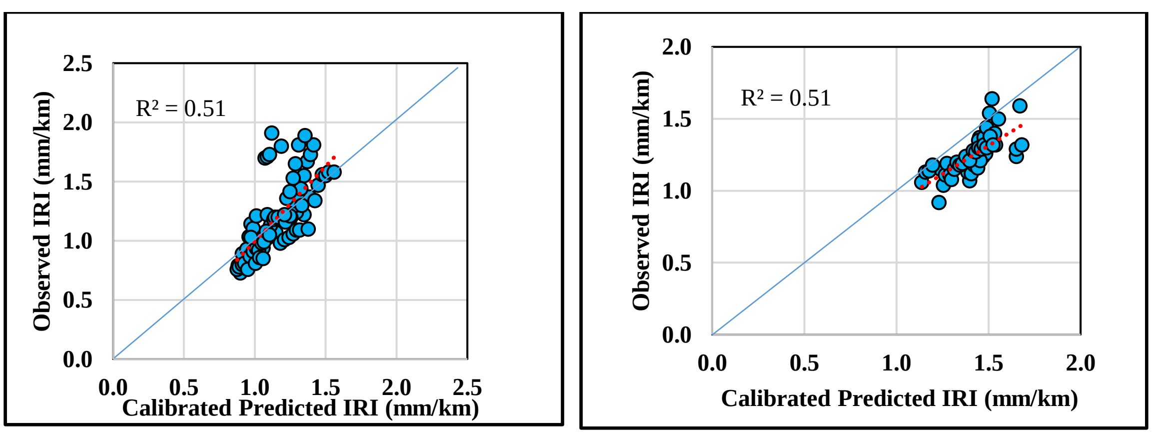
A similar scenario is found in Table 7.9. It is found that after clustering analysis, R^2 is improved and lower standard error is found for all calibrated models in case of permanent deformation.

The statistical significance of the calibrated models are also tested by comparing $F_{observed}$ value to $F_{critical}$ value (considering $\alpha = 0.05$) from the ANOVA of each model. All the models are found as statistically significant as $F_{observed} > F_{critical}$. Table 7.10 and Table 7.11 listed the $F_{observed}$ and $F_{critical}$ Values of IRI models and rut depth models respectively.

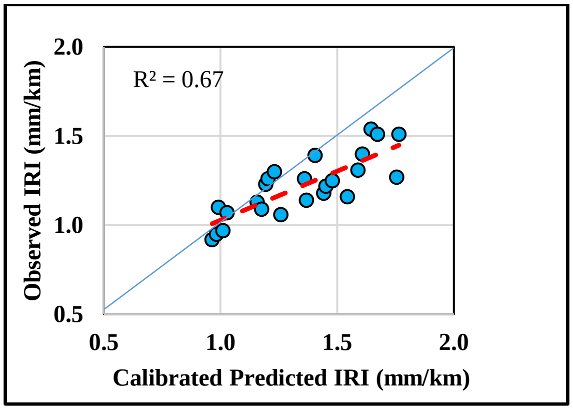
7.3.3 Validation Analysis of Calibrated Models

A validation analysis is conducted so that the calibrated models developed, dependent on the AC layer types, can produce accurate predictions of pavement distress. The validation process requires an independent data set not used in the calibration analysis. In this study, a 'split sample approach' is used for the validation analysis. The split sample approach splits the data set, with 80% used in calibration and 20% used for validation. The data set is split randomly in this research. However, since a full performance cycle is used in the analysis for each road section, validation data sets are not always exact and may exceed 20% in some cluster groups. For example, for IRI models of pavement sections with DFC, the validation data set is supposed to be 76 observations (20% of 382 observations). However, since the analysis for this road section considers all performance years of a full performance cycle, the validation data set counts a total of 83 observations for this category. In this way, the validation data set is formed for all cluster groups.

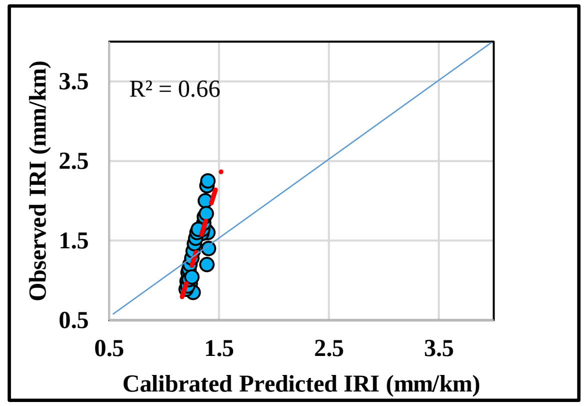
The predicted IRI and permanent deformation for each cluster group are corrected by using the respective calibration model. After calibration, these values are further compared to field observed values to investigate whether the 'goodness of fit' has improved accordingly. After comparison, the improved 'goodness of fit" is observed in both models of IRI and permanent deformation for all materials types. The improved R^2 value is observed for IRI and permanent deformation, which are presented in Figure 7.10 and Figure 7.11. In the ideal case, the observation points are supposed to be distributed over a 45-degree line. However, the data points of IRI and permanent deformation are distributed close to the 45-degree line and almost equally distributed between both sides of the line, thus confirming the validity of the calibration models for each cluster group.



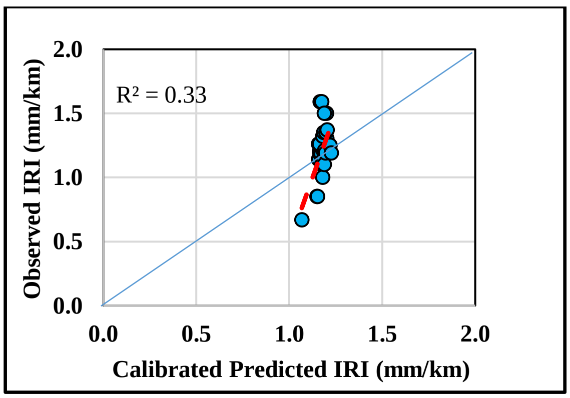
(a) (b)



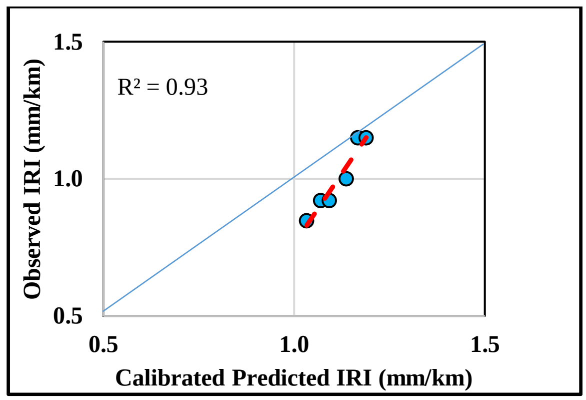
(c)



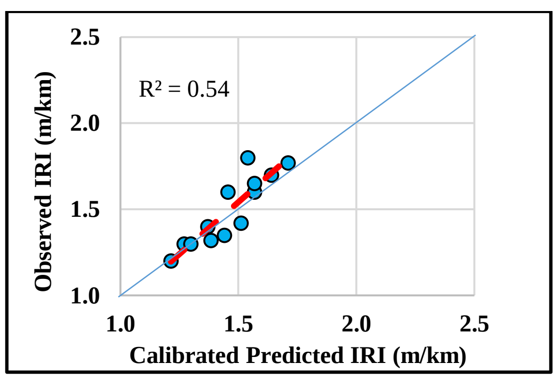
(d)



(e)



(f)

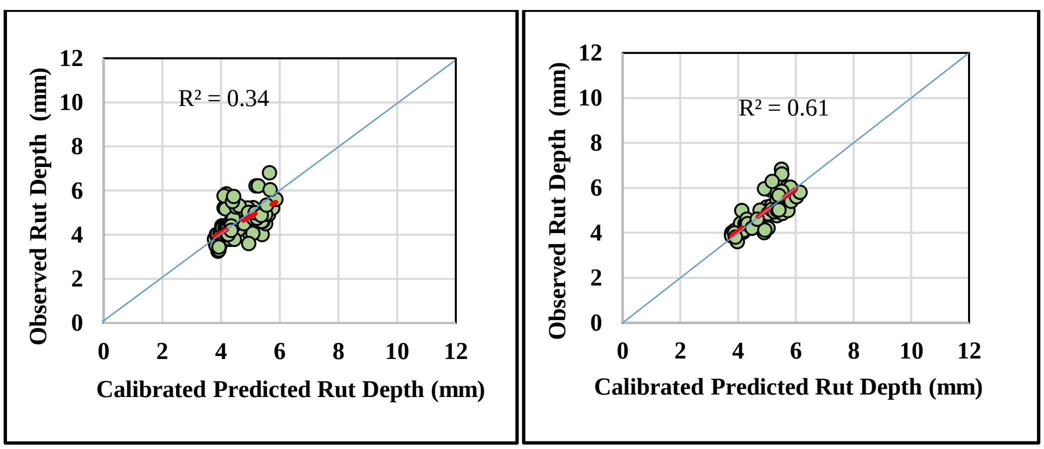


(g)

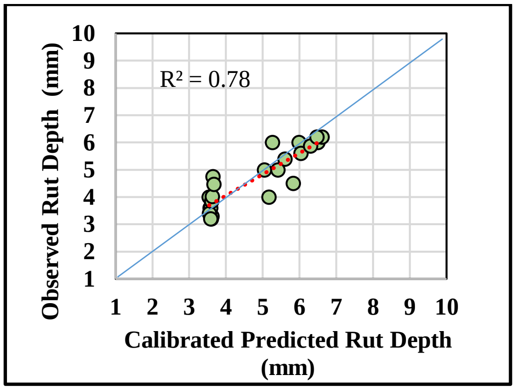
Figure 7.10: Comparison of Calibrated IRI to Field Observed Value for Pavement Sections with (a) DFC, (b) HL-1, (c) HL-3, (d) HL-3M, (e) HL-4, (f) HL-8, (g) Superpave Mixes

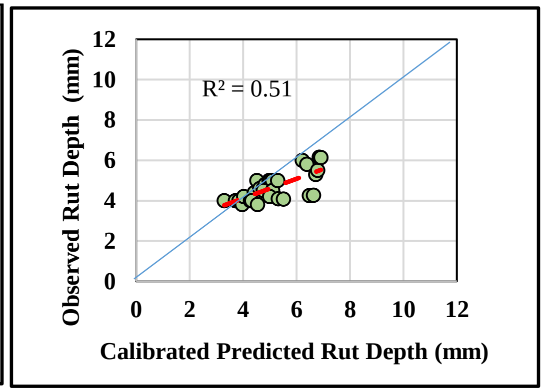
Table 7.10: Statistical Significance Test of IRI Models

Cluster Name	IRI Model	$F_{observed}$	$F_{critical}$	Significance
DFC	Calibrated Predicted IRI = 0.762x Predicted IRI + 0.258	231.91	3.87	Significant
HL1	Calibrated Predicted IRI = 0.489x Predicted IRI + 0.757	32.79	3.89	Significant
HL3	Calibrated Predicted IRI = 0.9199x Predicted IRI + 0.1088	95.88	3.94	Significant
HL3M	Calibrated Predicted IRI = 0.263x Predicted IRI + 0.9378	18.81	3.99	Significant
HL4	Calibrated Predicted IRI = 0.1256x Predicted IRI +1.044	9.12	4.00	Significant
HL8	Calibrated Predicted IRI = 0.7439x Predicted IRI + 0.3262	6.03	4.96	Significant
Superpave	Calibrated Predicted IRI = 1.42x Predicted IRI - 0.987	60.83	4.02	Significant



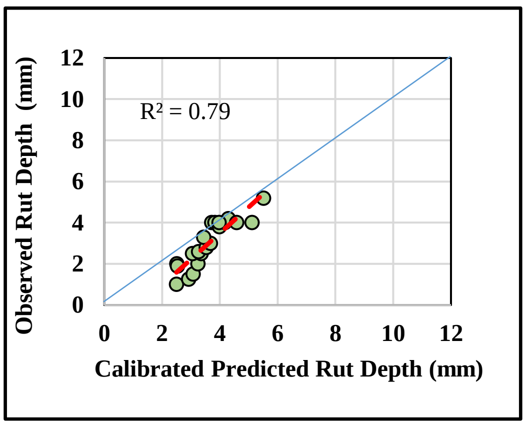
(a) (b)

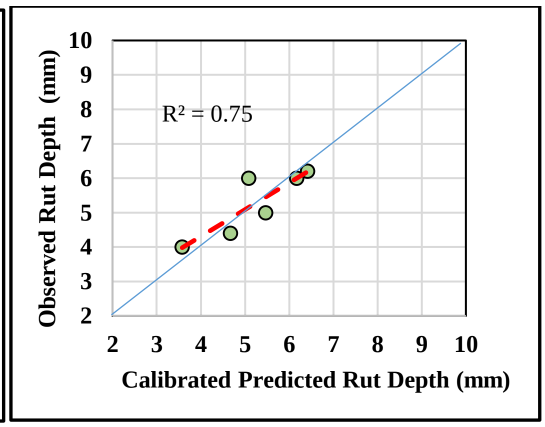




(c)

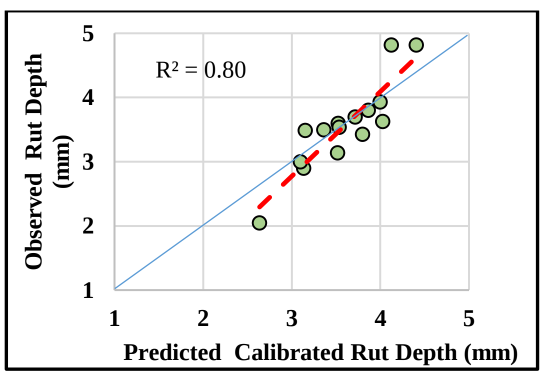
(d)





(e)

(f)



(g)

Figure 7.11: Comparison of Calibrated Rut Depth to Field Observed Value for Pavement Sections with (a) DFC, (b) HL-1, (c) HL-3, (d) HL-3M, (e) HL-4, (f) HL-8, (g) Superpave Mixes

Table 7.11: Statistical Significance Test of Permanent Deformation Models

Cluster Name	Permanent Deformation Model	$F_{observed}$	$F_{critical}$	Significance
DFC	Calibrated Predicted Permanent Deformation = 0.243x Predicted Permanent Deformation + 3.033	84.15	3.87	Significant
HL1	Calibrated Predicted Permanent Deformation = 0.227x Predicted Permanent Deformation + 3.64	32.79	3.88	Significant
HL3	Calibrated Predicted Permanent Deformation = 0.223x Predicted Permanent Deformation + 3.48	14.27	3.94	Significant
HL3M	Calibrated Predicted Permanent Deformation = 0.362x Predicted Permanent Deformation + 2.55	28.29	4.00	Significant
HL4	Calibrated Predicted Permanent Deformation = 0.365x Predicted Permanent Deformation + 1.8	7.75	4.06	Significant
HL8	Calibrated Predicted Permanent Deformation = 0.677x Predicted Permanent Deformation + 0.939	8.67	4.96	Significant
Superpave	Calibrated Predicted Permanent Deformation = 0.3576x Predicted Permanent Deformation + 0.575	34.76	4.06	Significant

7.4 Summary of Evaluation of Performance Predictions Using M-E Approach

This study investigates the performance of pavement sections through the M-E approach and compares it to the field-evaluated performance. The study is conducted by using historical pavement performance data from the MTO PMS-2.

Based on this analysis, it is found that most IRI and permanent deformation are over-predicted than those in field observations. However, bottom-up fatigue cracking portrays an entirely different picture with under-prediction compared to field evaluation.

Comparison of traffic levels and length of service life reveals that pavement sections with higher service life, exceeding 14 years, forecast predicted failure in IRI, total permanent deformation and AC permanent deformation. Failure in predicted permanent deformation is found for higher levels of traffic, regardless of the length of service life.

Although the M-E approach showed under-prediction of the bottom-up fatigue cracking, the lower level of fatigue resistance suggested by the master curve (compared to CPATT laboratory results) justifies the bottom-up fatigue failure in the field-observed scenario. These results show the need for local calibration of the prediction models of fatigue cracking and permanent deformation in the M-E approach. More importantly, the future maintenance strategy in the PMS requires consideration by addressing the fatigue responses of the highway sections.

The clustering regression analysis based on the surface layer confirms the improved goodness of fit for both IRI and permanent deformation. The validation process, with an independent data set, also confirms the validity of the calibrated models. Therefore, the predicted distresses based on the M-E approach are to be corrected further to ensure precise prediction.

The distresses predicted in this chapter are corrected accordingly and further investigated in the next chapter to develop the overall condition index model.

CHAPTER 8
DEVELOPING PREDICTION MODELS FOR ASSESSING OVERALL PAVEMENT CONDITIONS

In this chapter, prediction models are developed for assessing the overall condition by using a regression approach that considers the distresses predicted by the M-E approach. The deterioration of the overall pavement varies significantly depending on the traffic characteristics and material types. The deterioration model is estimated for three groups of AADT to recognize the influence of the difference in traffic and surface layer material properties. The time required for maintenance is also estimated for these categories.

The work of this chapter was presented at the Transportation Research Board (TRB) meeting 2017 (Jannat 2017). Part of this chapter was presented at the Transportation Association of Canada (TAC) Conference 2017 (Jannat 2017). Part of this chapter was also presented at the Transportation Association of Canada (TAC) Conference 2016 (Jannat 2016).

8.1 Introduction

The literature review in Chapter 2 and Chapter 3 confirms that in predicting the deterioration of pavement conditions, a generalized sigmoidal equation, irrespective of traffic and materials, is followed. It is also discussed in Chapter 3 that the predicted performance jump for any treatment is estimated generally based on engineering judgement. However, this jump depends on material types of the treatment applied. Moreover, the deterioration rate of the pavement varies significantly depending on the characteristics of traffic and the properties of materials (Prozzi 2001). In the same way, pavement service life and performance are found to be highly sensitive to traffic characteristics and pavement structure, which were investigated in Chapter 6. For this reason, the deterioration models should incorporate the effect of material properties and traffic characteristics. The M-E analysis will predict distress by considering local traffic and materials for specific road sections. Therefore, the performance index developed from the MEPDG-based distresses will overcome these limitations and in turn, improve the prediction of the pavement overall condition.

This chapter will develop the overall performance index model (for PCI and DMI) by incorporating distresses of the M-E approach. The performance deterioration curve (equation 3.1) will also be estimated based on traffic characteristics and material types.

8.2 Road Performance Data and Selected Road Sections

The experimental design consists of 128 highway sections. These highway sections consist of 113 sections with Marshall mixes and 15 sections with Superpave mixes. In this study, a total of 161 performance cycles are investigated for predicting pavement performance deterioration patterns.

8.3 Developing Prediction Models to Assess the Overall Pavement Condition
This chapter focuses on developing an overall performance index based on the distresses predicted in the M-E approach, and estimating the deterioration models for different ranges of AADT and material types.

The highway sections are investigated for performance over the performance cycle. After predicting the distresses, the overall performance index model is estimated by the regression analysis that considers the MEPDG distresses. A statistical significance test is carried out for the estimated model. The traffic is categorized based on the range of the AADT, which is observed on the selected highways. The material types used in the cluster analysis in the previous chapter are under investigation in this chapter. The deterioration models are estimated based on the AADT ranges and material types of the existing pavement structure. Figure 8.1 shows the steps in the methodology.

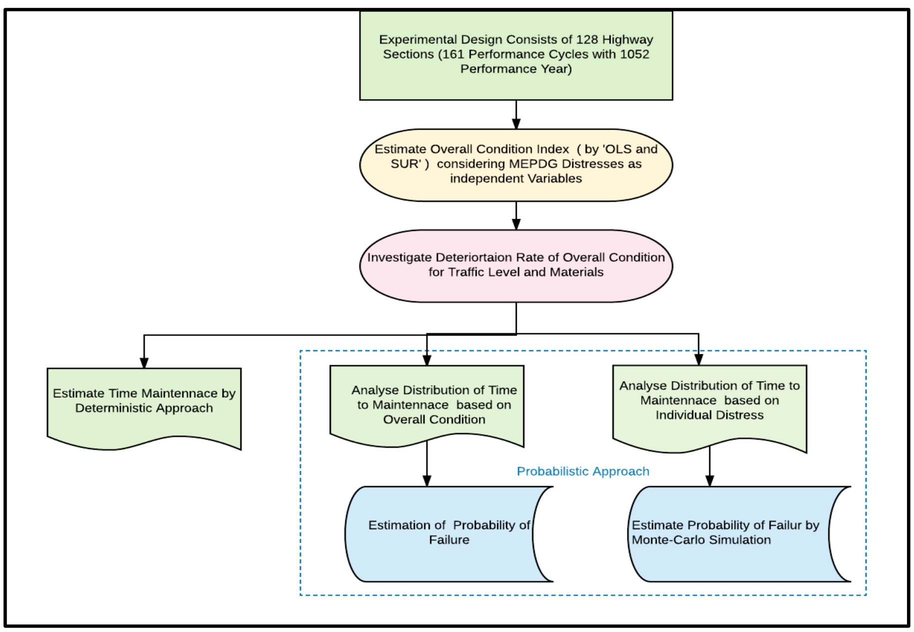


Figure 8.1: Steps for Developing Prediction Model for Assessing the Overall Condition of Pavement

8.3.1 Estimation of Overall Performance Index Model
As discussed in Chapter 4, composite indices, including DMI and PCI are used to quantify the condition of roads on Ontario highways over time. The PCI is a function of roughness, rut depth and DMI (refer to equation 4.2), while the factors making up the DMI are thermal cracking, AC

bottom-up fatigue cracking and AC top-down fatigue cracking. Similar independent variables used in Ontario's DMI and PCI models are considered in the study. However, this study considers the predicted distresses from the M-E approach as independent variables, while field-evaluated distresses are used in case of field evaluated PCI models.

The prediction models in this study are estimated by using the OLS approach. However, pavement deterioration may be affected by many factors. These unobserved factors influencing pavement performance may be correlated or not. Since the investigation in Chapter 5 confirms that the unobserved factors in PCI and DMI are highly correlated, there is a chance that the OLS may not be able to retrieve unbiased parameter estimates for the regression models. For this reason, this study also estimated the models by using the SUR approach to capture the deterioration process of pavement performance.

After the regression analysis, the estimated model is found as:

$$\begin{aligned} DMI\ by\ OLS\ &= 7.741 + 2.344\ Scaled\ Predicted\ Bottom\ up\ Fatigue\ Cracking + \\ &\quad 0.671\ Scaled\ Predicted\ Top\ Down\ Fatigue\ Cracking + \\ &\quad 0.046 Scaled\ Predicted\ Thermal\ Cracking \end{aligned} \tag{8.1}$$

Where,

Scaled Predicted Bottom up Fatigue Carking= Predicted Bottom-up Fatigue Carking /25 (%)

Scaled Predicted Top Down Fatigue Cracking= Predicted Top Down Fatigue Cracking/378.80 (m/km)

Scaled Predicted Thermal Cracking = Predicted Thermal Cracking /189.40 (m/km)

$$\begin{aligned} DMI\ by\ SUR\ &= 7.739 + 2.448\ Scaled\ Predicted\ Bottom\ up\ Fatigue\ Cracking \\ &\quad + \quad 0.679\ Scaled\ Predicted\ Top\ Down\ Fatigue\ Cracking \\ &\quad + \quad 0.051 Scaled\ Predicted\ Thermal\ Cracking \end{aligned} \tag{8.2}$$

$$\begin{aligned} PCI\ by\ OLS &= 29.733 - 16.384\ Scaled\ Predicted\ IRI\ - \\ &\quad 1.46\ \ Scaled\ Predicted\ \ Permanent\ Deformation\ + 4.644\ DMI \end{aligned} \tag{8.3}$$

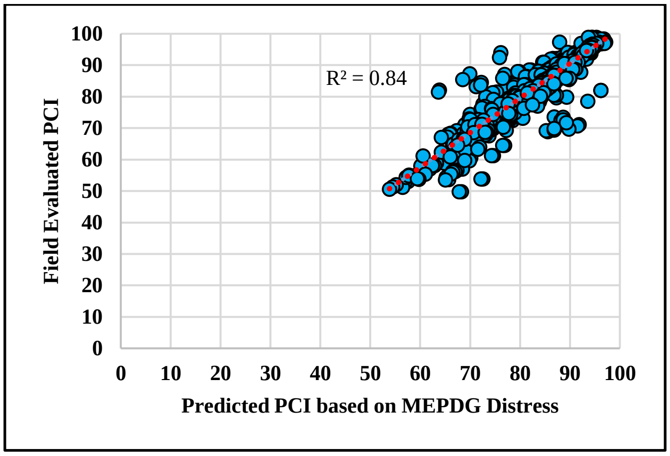
$$\begin{aligned} PCI\ by\ SUR &= 28.256 - 16.32\ Scaled\ Predicted\ IRI\ - \\ &\quad 1.446\ \ Scaled\ Predicted\ Rut\ Depth + 7.54\ DMI \end{aligned} \tag{8.4}$$

Where,

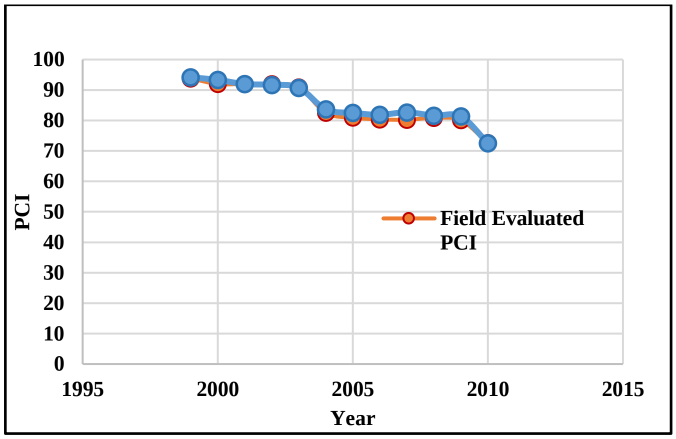
Scaled Predicted IRI= Predicted IRI/2.30 (m/km) (for arterials)

= Predicted IRI/1.90 (m/km) (for freeways)

Sacled Predicted Permanent Deformation Total =Predicted Permanent Deformation Total/ 19.0 (mm)



(a)



(b)

Figure 8.2: Comparison of Predicted PCI to Field Evaluated PCI (a) for all Road Sections, (b) for one Section of Highway 6 over the Performance Cycle

The significance of the PCI model is tested by comparing F_{obs} value (307 from the model) to $F_{critical}$ value. Considering $\alpha = 0.05$: $F_{critical} = F_{\alpha\,,\,p-1=3,\;n-p=247,} = 2.65$. It is found that $F_{obs} > F_{critical}$. Therefore, the model is significant. The t_{obs} for each parameter is compared to $t_{critical\ for\ 0.025,n-p=247} = 1.97$. Therefore, the estimated parameters are significant too.

The predicted PCI is further compared to the field-evaluated PCI for all sections to examine the ‘goodness of fit’. This performance comparison for one highway section (one section of highway 6 from the year 1998 to 2012) is presented in Figure 8.2. Figure 8.2 shows that the performance predicted by the model is close to actual field-evaluated PCI and following a similar pattern of the actual conditions.

8.3.2 Overall Condition based on the Traffic and Materials

It is observed that the AADT in the first year of the performance varies from 5,000 to 138,000 for the highway sections with Marshall mixes, and from 8,000 to 171,000 for the highway sections with Superpave mixes. The performance cycle of the road sections varies from four to 18 years for the highway sections with Marshall mixes, and four to 15 years for the highway sections with Superpave. Figure 8.3 shows the distribution of the AADT and performance cycle of the highway sections with Marshall mixes and Superpave mixes. The distribution pattern of AADT, AADTT and traffic growth factors are also discussed in Chapter 7.

The traffic in Ontario is categorized as A, B, C, D and E (low to high volume) depending on the Equivalent Single Axle Load (ESAL) for the projected traffic level expected in the design lane over a 20-year period, regardless of the actual design life of the pavement. The projected ESALs of the selected highway sections over the 20-year period are found to be more than 30 million, which are considered as high-traffic volume or category 'E' (OHMPA 2007).

From Figure 8.3, it is observed that approximately 50% of the highway sections are with AADT of 25,000 or less, 20% of the highways are with AADT between 25,000 to 50,000 and 30% of the highways are with AADT over 50,000 for road sections with Marshall mixes. A comparable scenario is observed in the highway sections with Superpave mixes too. In the case of road sections with Superpave mixes, approximately 43% of the highway sections are with AADT of 25,000 or less, 12% of the highway sections are with AADT from 25,000 to 50,000 and 45% of the highways are with AADT over 50,000. Since all the highways sections are found with high-traffic volume, the sections are further categorized based on the level of AADT in the first year of performance. Table 8.1 shows the category of AADT that is followed in this research.

Table 8.1: Traffic Category

Category	**AADT in First Year of Performance**
Low High	≤25,000
Medium High	>25,000 to ≤ 50,000
Very High	>50,000

Table 8.2: Average Improvement in PCI for Treatment Types

Material Type	Initial PCI	
	Average	Standard Deviation
DFC	93	4.1
HL1	92	4.4
HL3	91	4.5
HL3M	91	4.9
HL4	90	5.4
HL8	90	6.5
Superpave (SP12.5 FC2)	94	7.1

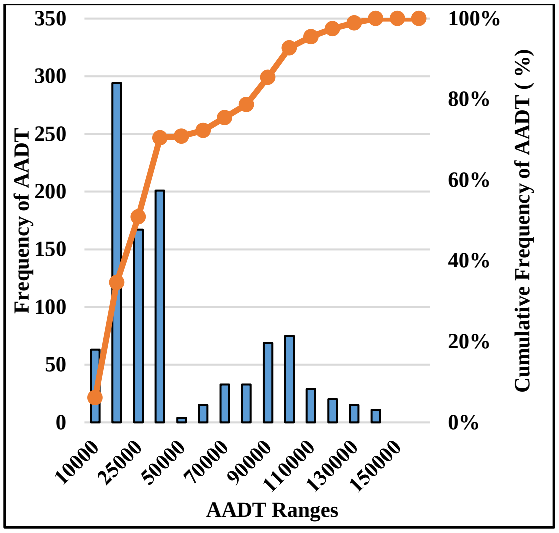
From the PMS-2 database, the layers of the existing pavement structure are investigated. As discussed in Chapter 7 that the pavement structure of the selected highway sections with Marshall mix design is mainly found as resurfaced with DFC and different types of HL asphalt surface, these materials types are used in estimation of deterioration models.

The improvement of PCI after applying a certain treatment, in terms of the type of materials, is also estimated by the prediction model. With the responses of the MEPDG-based pavement distresses in the first year of the performance cycle, the improved performance is estimated for that certain material types. The improved PCI value for material types is summarized in Table 8.2. Table 8.2 shows that the improvement in the PCI for overlay with Superpave mixes (PCI 94) and DFC (PCI 93) are higher than in PCI for the other HL layer.

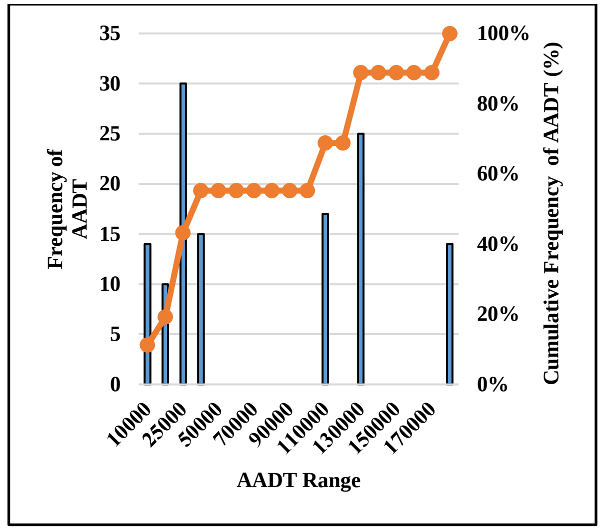
8.3.3 Deterioration of Overall Condition Based on Traffic and Materials

Generally, the future deterioration pattern of the overall pavement condition over the time is calculated based on a general prediction model, which is a sigmoidal form with different model coefficients (TAC 2013). The sigmoidal curve is followed to predict the future deterioration of Ontario highways (equation 3.1) (Kazmierowski 2001, TAC 2013 and Ningyuan 2001).

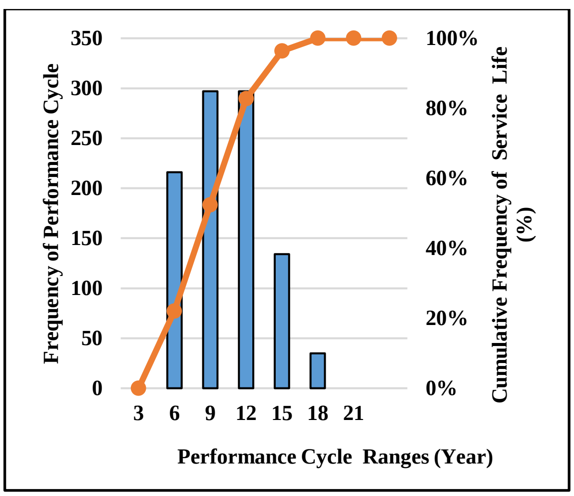
Depending on the model coefficients, the shape of the performance curve may be a straight line, convex, concave or S-shaped, with varying degrees of curvature. With this flexibility offered by the curve, the coefficients of the models are estimated to fit into different pavement performance deterioration trends due to change in AADT and properties of pavement materials. The model coefficients are determined automatically using the least squares, nonlinear regression method. The coefficients of the equation 3.1 (discussed in Chapter 3) are estimated in this study for field-evaluated scenarios and predicted scenarios by the M-E approach.



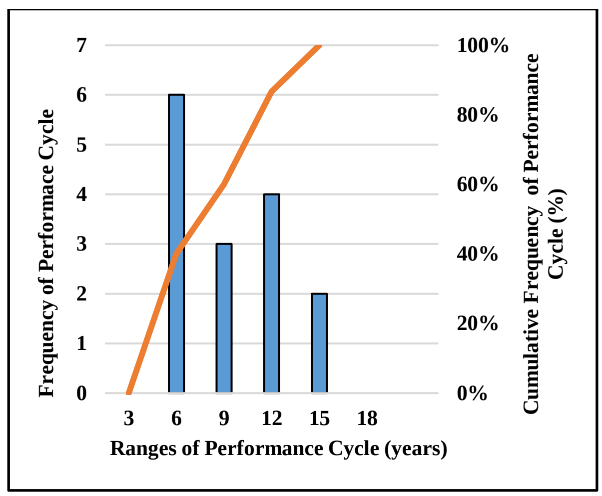
(a)



(b)



(c)



(d)

Figure 8.3: Histogram of (a) AADT for Sections with Marshall Mixes; (b) AADT for Sections with Superpave Mixes, (c) Performance Cycles of Sections with Marshall Mixes (d) Performance Cycles of Sections with Superpave Mixes

After estimating the coefficients of each model, analysis of variance (ANOVA) shows that all the models are significant (as the $F_{observed}$ value is found as higher than the $F_{critical}$ value) and the parameters of the respective models are significant (as the $t_{observed}$ is found as higher than the

$t_{critical}$) too. For the three cases (HL3 with AADT 25,000 to 50,000; HL4 with AADT 25,000 to 50,000 and HL8 with AADT 25,000 to 50,000), the least squares method could not complete the iteration due to the limited number of observations. For these three categories, both prediction models are plotted and calibrated against the actual field-evaluated condition over the performance cycle. For all other categories, both models are plotted and compared to field-evaluated PCI value over the performance cycle. Figure 8.4 presents the comparison of both models to the actual field-evaluated PCI for DFC (with AADT >50,000). The estimated coefficients of all the models are listed in Table 8.3.

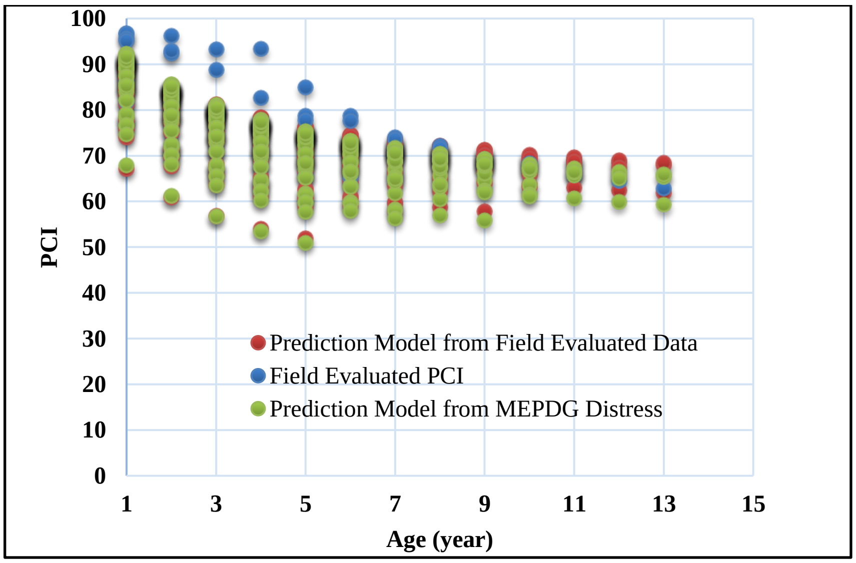


Figure 8.4: Comparison of the Predicted models to Field-Evaluated PCI for DFC with AADT >50,000.

Since the estimated coefficients of the model for different traffic levels offer a variation on similar materials, this will impact the service life and the respective time to maintenance requirements. For this reason, the time to maintenance requirements is estimated by considering the maintenance requirement trigger value of PCI. The maintenance requirement is triggered when PCI deteriorates to a level below 65. The expected time of maintenance for each category is depicted in Table 8.4. Table 8.5 and 8.6 listed the average time to maintenance along with standard deviation in the case of field observation and predicted by the M-E approach respectively.

Table 8.3: Estimated Coefficients of the Pavement Deterioration Model

Surface Material Type	AADT	Coefficients of PCI Model Based on Field-Evaluated Value: $P = P_0 - 2e^{(a-bc^t)}$			Coefficient of PCI Model Based on the M-E Approach: $P = P_0 - 2e^{(a-bc^t)}$		
		a	**b**	**c**	**a**	**b**	**c**
DFC	≤25,000	2.369	4.746	2.786	2.888	4.417	2.009
	>25,000 to ≤ 50,000	2.750	4.500	3.600	2.800	4.500	3.600
	>50,000	2.980	1.910	2.000	3.110	2.170	2.000
HL1	≤25,000	4.396	5.594	1.521	3.170	5.249	1.971
	>25,000 to ≤ 50,000	4.418	5.144	1.429	3.559	4.783	1.668
	>50,000	N/A[11]			N/A		
HL3	≤25,000	2.990	6.230	2.939	4.394	5.668	1.610
	>25,000 to ≤ 50,000	4.570	5.500	1.570	4.580	5.660	1.581
	>50,000	N/A			N/A		
HL3M	≤25,000	2.590	5.630	2.900	2.632	6.416	3.171
	>25,000 to ≤ 50,000	N/A			N/A		
	>50,000	N/A			N/A		
HL4	≤25,000	7.229	9.249	1.364	6.956	8.670	1.364
	>25,000 to ≤ 50,000	7.345	8.780	1.340	7.420	8.790	1.341
	>50,000	N/A			N/A		
HL8	≤25,000	1.866	15.361	16.865	1.928	15.538	16.050
	>25,000 to ≤ 50,000	2.369	4.746	2.786	2.425	4.800	2.779
	>50,000	N/A			N/A		
Superpave (SP 12.5 FC2)	≤25,000	2.369	4.746	2.786	2.888	4.417	2.009
	>25,000 to ≤ 50,000	2.650	2.400	1.900	2.690	2.300	1.890
	>50,000	2.880	2.386	1.869	2.903	2.400	1.900

[11] N/A=Not Available

Table 8.4: Summary of Expected Time to Maintenance

Surface Material Type	AADT	Expected Time to Maintenance (Year)	
		PCI Model Based on Field-Evaluated Value	PCI Model Based on M-E Approach
DFC	≤25,000	17	15
	>25,000 to ≤ 50,000	14	12
	>50,000	12	9
HL1	≤25,000	14	17
	>25,000 to ≤ 50,000	13	13
	>50,000	N/A[12]	N/A
HL3	≤25,000	12	10
	>25,000 to ≤ 50,000	9	9
	>50,000	N/A	N/A
HL3M	≤25,000	11	10
	>25,000 to ≤ 50,000	N/A	N/A
	>50,000	N/A	N/A
HL4	≤25,000	8	8
	>25,000 to ≤ 50,000	7	7
	>50,000	N/A	N/A
HL8	≤25,000	7	7
	>25,000 to ≤ 50,000	6	6
	>50,000	N/A	N/A
Superpave (SP 12.5 FC2)	≤25,000	17	16
	>25,000 to ≤ 50,000	16	15
	>50,000	14	13

8.4 Results of Deterministic Approach

The prediction models are estimated by using the OLS approach as well as the SUR approach in this study. The PCI model is similar in both approaches. The model is found as statistically significant too. The significance of the PCI model is tested by comparing the $F_{observed}$ value to $F_{critical}$ value and is found as significant. The estimated parameters are tested for statistical significance by comparing the $t_{observed}$ of each parameter to $t_{critical}$ and are found as significant. The IRI is found with a higher value of coefficient compared to the coefficient of rut depth or permanent deformation and DMI. The existing model confirms a similar trend too.

[12] N/A= Not available

The predicted PCI is further compared to the field-evaluated PCI for all sections to examine the 'goodness of fit' and is consistent. The plot of field-evaluated versus predicted PCI (SUR approach) in Figure 8.2 (a) presents the 'goodness of fit' with the $R^2 = 0.84$.

To detect the difference in the predicted performance by the model, the predicted PCI is plotted against actual field-observed PCI over a continuous road segment (one section of Highway 6) for a performance cycle of 15 years (1998 to 2012) in Figure 8.2 (b). This figure clarifies that the performance predicted by the model is close to the actual field-evaluated PCI.

The selected highway sections are found with high-traffic volume (category 'E') and thus are further categorized into three groups based on the distribution of the AADT shown in Figure 8.3. From Figure 8.3, it is observed that about 50% of the highway sections (50% for the sections Marshall mixes and 43% for the sections with Superpave mixes) are with AADT of 25,000 or less. They are categorized into three groups, listed in Table 8.1, to recognize the influence due to the difference in AADT on the deterioration prediction models.

From Table 8.2, it is observed that the improvement in PCI for the overlay of Superpave (PCI 94) and DFC (PCI 93) are higher than in PCI for the other HL layer.

All the deterioration models are found as significant (as the $F_{observed}$ value is found as higher than the $F_{critical}$ value) and the parameters of the respective model are significant (as the $t_{observed}$ is found as higher than the $t_{critical}$) too. For the cases of HL3 with AADT 25,000 to 50,000, HL4 with AADT 25,000 to 50,000 and HL8 with AADT 25,000 to 50,000, the least squares method could not complete the iteration due to the limited number of observations. However, prediction models are plotted and calibrated against the actual field-evaluated condition over the performance cycle.

Figure 8.4 reveals that the deterioration of PCI predicted by the models from the field-evaluated PCI and MEPDG-based distresses are following the patterns close to the actual field-evaluated PCI over the performance cycle (for DFC with AADT >50,000). A similar scenario is observed for other prediction models.

The models could not be estimated for cases of AADT more than 50,000 in HL-1, HL-3, HL-3M, HL-4 and HL-8 due to the limitation of an available number of observations.

The expected time to maintenance presented in Table 8.4 reveals that overlay with DFC and Superpave will require maintenance requirements later than other HL layers. However, the level of AADT affects the required time to maintenance from 15 to 9 years in DFC for low AADT to high AADT. For the road sections with Superpave mixes, the required time to maintenance varies from 16 to 13 years for low AADT to high AADT. HL-8 requires early maintenance (6 to 7 years) than other HL types. It is also found that the estimated time for maintenance of most categories, except HL1 with AADT ≤ 25,000, in the M-E approach, is equal or lower than in field-evaluated PCI. This may happen, as the distresses predicted by the M-E approach are over-predicted in most cases.

Table 8.5: Average Expected Time to Maintenance for PCI Model Based on Field Evaluation

Surface Material Type	AADT	Time to Maintenance/Failure from Distribution (Year)		
		Based on Field Observation	Standard Deviation	Coefficient of Variation
DFC	≤25,000	17.0	7.24	0.43
	>25,000 to ≤ 50,000	14.0	2.87	0.21
	>50,000	13.2	7.63	0.58
HL1	≤25,000	13.7	4.64	0.34
	>25,000 to ≤ 50,000	13.0	2.86	0.22
	>50,000	N/A		
HL3	≤25,000	13.2	5.32	0.40
	>25,000 to ≤ 50,000	9.0	1.54	0.17
	>50,000	N/A		
HL3M	≤25,000	10.8	3.28	0.30
	>25,000 to ≤ 50,000	N/A		
	>50,000	N/A		
HL4	≤25,000	9.1	1.26	0.14
	>25,000 to ≤ 50,000	6.7	0.81	0.12
	>50,000	N/A		
HL8	≤25,000	7.0	0.90	0.13
	>25,000 to ≤ 50,000	6.4	0.89	0.14
	>50,000	N/A		
Superpave (SP 12.5 FC2)	≤25,000	16.8	1.60	0.10
	>25,000 to ≤ 50,000	15.9	2.98	0.19
	>50,000	14.2	7.56	0.53

Table 8.6: Average Expected Time to Maintenance Based on M-E Approach

Surface Material Type	AADT	Time to Maintenance /Failure from Distribution (Year)		
		Based on M-E Approach	Standard Deviation	Coefficient of Variation
DFC	≤25,000	14.9	6.31	0.42
	>25,000 to ≤ 50,000	12.3	2.69	0.22
	>50,000	9.1	4.11	0.45
HL1	≤25,000	16.4	7.54	0.46
	>25,000 to ≤ 50,000	13.1	3.28	0.25
	>50,000	N/A		
HL3	≤25,000	10.7	2.43	0.23
	>25,000 to ≤ 50,000	9.0	1.46	0.16
	>50,000	N/A		
HL3M	≤25,000	9.5	2.51	0.26
	>25,000 to ≤ 50,000	N/A		
	>50,000	N/A		
HL4	≤25,000	8.9	1.31	0.15
	>25,000 to ≤ 50,000	6.7	0.82	0.12
	>50,000	N/A		
HL8	≤25,000	7.1	1.29	0.18
	>25,000 to ≤ 50,000	5.7	0.74	0.13
	>50,000	N/A		
Superpave (SP 12.5 FC2)	≤25,000	16.2	1.23	0.08
	>25,000 to ≤ 50,000	14.7	2.36	0.16
	>50,000	12.6	6.041	0.4779

8.5 Probabilistic Approach on Deterioration of Overall Condition

The expected time to maintenance is estimated for all observations in Table 8.5 and Table 8.6. The time to maintenance estimated by the deterministic approach can further be investigated with a probabilistic analysis to ensure that the estimate is realistic and reasonably probable. For this reason, a probabilistic approach is applied to estimate the probability of failure.

The distribution of time to failure or maintenance may vary depending on the material types and traffic. For this reason, the distribution of time to maintenance is plotted for each category to identify the type of distribution. For both field-observed and M-E approach cases, probability paper plots are compared for each category and distribution types are selected. Figure 8.5 shows the probability plots for DFC (for AADT >50000) for field-evaluated PCI. It is found that the Weibull distribution is the best fit for this category. For all other categories of traffic and materials, the 'best-fit' distribution of time to maintenance is identified accordingly. The distribution parameters are estimated from the probability paper plot and following the method of moments for Weibull distribution. Table 8.7 summarizes the distribution parameters for all categories for the field-observed cases. Table 8.8 summarizes the distribution parameters for all categories for the M-E approach. The highest R^2 value of the 'best fit' distribution for each sub-category is shown in bold font in Table 8.7 and Table 8.8.

In solving the following equations, the distribution parameters for the respective distributions are estimated.

For normal distribution, the Probability Density Function (PDF) is calculated by using the following equation (Benjamin 1970; Ang 1975 and Pandey 2014):

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad -\infty \leq x \leq \infty \qquad (8.6)$$

Where,
μ= mean of distribution or location parameter
σ = standard deviation or scale parameter

For exponential distribution, the PDF is calculated by using the following equation:

$$f(x) = \lambda\, e^{-\lambda x} \qquad (8.7)$$

Where,
λ= scale parameter and $x > 0$

The Cumulative Distribution Function (CDF) of exponential distribution is calculated by using the following equation:

$$F(x) = 1 - e^{-\lambda x} \qquad (8.8)$$

For log-normal distribution, the PDF is calculated by using the following equation:

$$f(x) = \frac{1}{\sqrt{2\pi x\zeta}} e^{\frac{-(lnx-\lambda)^2}{2\zeta^2}} \quad x \geq 0;\ \zeta > \infty \qquad (8.9)$$

Where,
ζ = shape parameter or slope

λ= scale parameter or intercept

CDF of the log-normal distribution is calculated by using the following equation:

$$F_X(x) = \int_{-\infty}^{x} f_X(x)dx = \phi\left(\frac{lnx-\lambda}{\zeta}\right) \quad (8.10)$$

$$\lambda = \ln(\mu) - \frac{1}{2}\zeta^2 \quad (8.11)$$

$$\zeta = \sqrt{ln(1+\delta^2)} \quad (8.12)$$

Where,
$\delta =$ coefficient of variation

The PDF of the Weibull distribution is calculated by using the following equation:

$$f(x) = \frac{\alpha}{\beta^{\alpha}} x^{\alpha-1} e^{-(\frac{x}{\beta})^{\alpha}} \quad (8.13)$$

Where,
$\alpha =$shape parameter or slope,
β = scale parameter or intercept

$$\text{mean}, \bar{x} = \beta\Gamma\left(1+\frac{1}{\alpha}\right)$$

$$\text{Standard deviation}, s = \beta\sqrt{\Gamma\left(1+\frac{2}{\alpha}\right) - \Gamma\left(1+\frac{1}{\alpha}\right)^2}$$

Γ= gamma function

The CDF of the Weibull distribution is calculated by using the following equation:

$$F(t) = 1 - e^{-\left(\frac{t}{\beta}\right)^{\alpha}} \quad (8.14)$$

The Weibull reliability function is calculated by using the following equation:

$$R(t) = e^{-(\frac{t}{\beta})^{\alpha}} \quad (8.15)$$

The Weibull hazard rate function is calculated by using the following equation:

$$h(t) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \quad (8.16)$$

Where,
T = age
$\alpha =$shape parameter or slope,
β = scale parameter or intercept

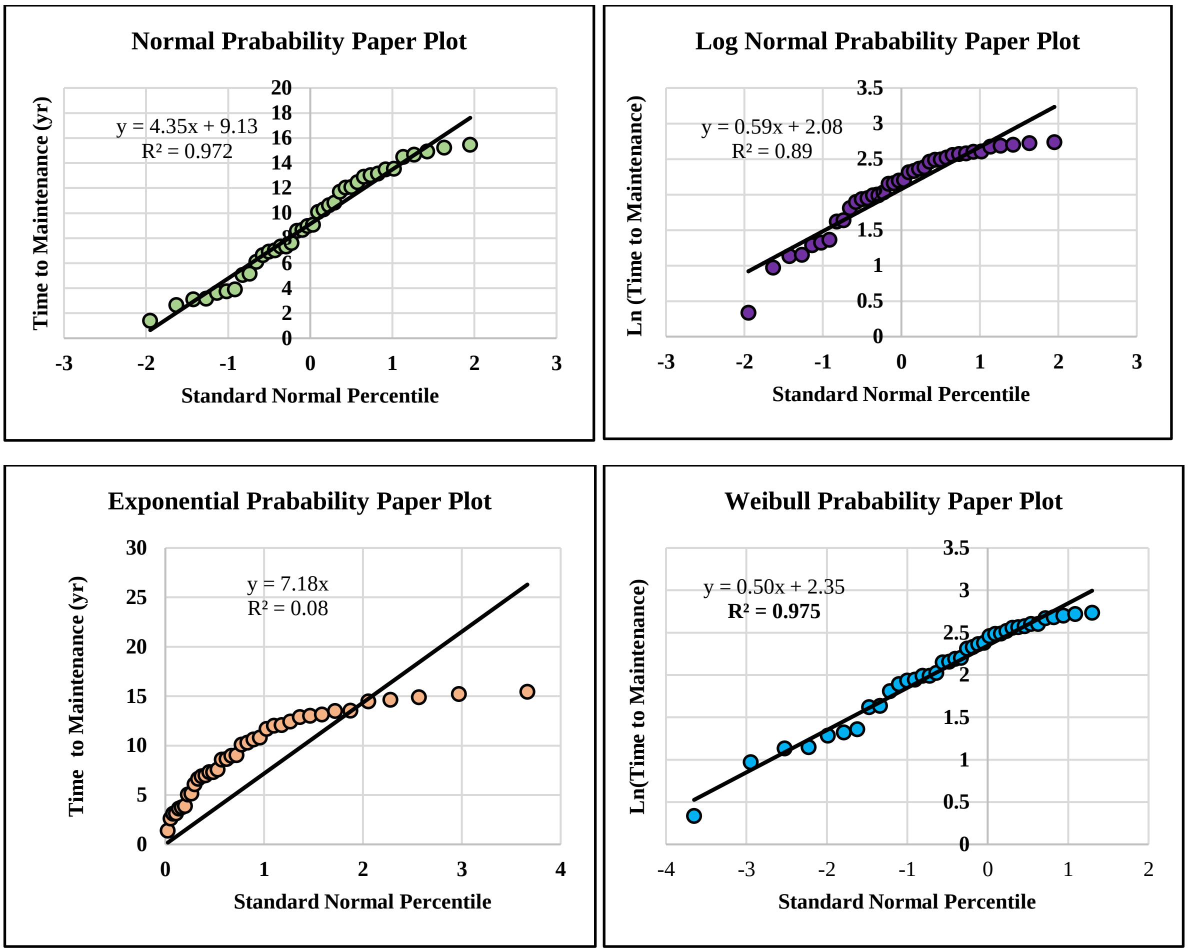


Figure 8.5: Probability Paper Plot of Time to Maintenance for DFC (AADT >50,000) for PCI model based on Field Evaluated Value

It is observed from Table 8.7 that for most of the categories, the distribution of the time to maintenance is 'best fit' by the Weibull distribution. However, the normal distribution is found as 'best fit' for HL1 with AADT ≤25,000, HL3 with AADT ≤25,000, and HL-8 with AADT ≤25,000. The log-normal distribution is found as 'best-fit' for sections with Superpave mixes with AADT >50,000. The exponential distribution is also found as 'best- fit' for only one category of HL-3M with AADT ≤25,000.

Table 8.7: Distribution Parameters of Time to Maintenance for PCI based on Field-Evaluated Values

Surface Material Type	AADT	Normal Distribution			Log-Normal Distribution			Exponential Distribution		Weibull Distribution				
		R^2	Location	Scale Parameter	R^2	Scale Parameter	Shape Parameter	R^2	Scale Parameter	R^2	Scale Parameter from Probability Paper Plot	Shape Parameter from Probability Paper Plot	Scale Parameter by Method of Moments	Shape Parameter by Method of Moments
DFC	≤25,000	0.863	17.021	7.238	0.802	0.408	2.751	0.065	0.059	**0.867**	19.853	1.855	19.181	2.518
	>25,000 to ≤ 50,000	0.669	14.024	2.873	0.625	0.203	2.620	-6.270	0.071	**0.730**	15.256	4.437	15.168	5.649
	>50,000	0.972	13.226	7.627	0.898	0.429	2.120	0.084	0.109	**0.975**	10.457	2.004	10.305	2.366
HL1	≤25,000	**0.970**	13.707	4.639	0.901	0.329	2.564	0.932	0.073	0.968	15.454	2.822	15.292	3.248
	>25,000 to ≤ 50,000	0.901	12.950	2.861	0.835	0.218	2.537	-4.691	0.077	**0.917**	14.212	4.196	14.073	5.201
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL3	≤25,000	**0.958**	13.174	5.320	0.944	0.389	2.503	0.213	0.076	0.955	14.989	2.380	14.820	2.667
	>25,000 to ≤ 50,000	0.765	9.016	1.544	0.727	0.170	2.185	-10.240	0.111	**0.840**	9.690	5.711	9.648	6.859
	>50,000		N/A											
HL3M	≤25,000	0.983	10.798	3.280	0.968	0.297	2.335	**0.989**	0.093	0.984	12.099	3.135	11.972	3.663
	>25,000 ≤ 50,000		N/A											
	>50,000		N/A											
HL4	≤25,000	0.850	9.089	1.258	0.795	0.138	2.198	-15.320	0.110	**0.868**	9.667	6.807	9.617	8.619
	>25,000 to ≤ 50,000	0.792	6.655	0.806	0.774	0.121	1.888	-21.800	0.150	**0.870**	7.022	7.962	6.998	9.926
	>50,000		N/A											
HL8	≤25,000	**0.747**	7.047	0.901	0.775	0.127	1.944	-17.520	0.142	0.740	7.382	8.993	7.428	9.371
	>25,000 to ≤ 50,000	0.856	6.371	0.891	0.834	0.139	1.842	-13.900	0.157	**0.901**	6.798	6.258	6.745	8.517
	>50,000		N/A											
Superpave(SP 12.5 FC2)	≤25,000	0.645	16.823	1.602	0.642	0.095	2.818	-38.110	0.059	**0.746**	17.509	10.799	17.514	12.790
	>25,000 to ≤ 50,000	0.753	15.862	2.981	0.732	0.186	2.747	-6.563	0.063	**0.807**	17.245	4.511	17.066	6.203
	>50,000	0.850	14.159	7.563	**0.935**	0.501	2.525	0.815	0.071	0.888	16.260	1.908	15.968	1.952

Table 8.8: Distribution Parameters of Time to Maintenance for PCI based on M-E Approach

Surface Material	AADT	Normal Distribution			Log-Normal Distribution			Exponential Distribution		Weibull Distribution				
		R^2	Location	Scale Parameter	R^2	Scale Parameter	Shape Parameter	R^2	Scale Parameter	R^2	Scale Parameter from Probability Paper Plot	Shape Parameter from Probability Paper Plot	Scale Parameter by Method of Moments	Shape Parameter by Method of Moments
DFC	≤25,000	**0.88**	14.92	6.31	0.81	0.41	2.62	0.07	0.07	**0.88**	17.34	1.86	16.81	2.53
	>25,000 to ≤ 50,000	0.86	12.25	2.69	0.81	0.22	2.48	-4.50	0.08	**0.89**	13.48	3.98	13.31	5.24
	>50,000	0.97	9.13	4.11	0.90	0.43	2.12	0.08	0.11	**0.98**	10.46	2.00	10.31	2.37
HL1	≤25,000	0.96	16.40	7.54	0.95	0.44	2.70	0.37	0.06	**0.98**	18.64	2.17	18.51	2.31
	>25,000 to ≤ 50,000	**0.96**	13.05	3.28	0.90	0.25	2.54	-2.78	0.08	0.95	14.44	3.75	14.30	4.51
	>50,000		N/A											
HL3	≤25,000	**0.93**	10.68	2.43	0.86	0.23	2.34	-3.99	0.09	0.92	11.72	4.13	11.63	5.03
	>25,000 to ≤ 50,000	0.76	9.50	2.51	0.72	0.16	2.19	-11.66	0.11	**0.83**	9.68	6.11	9.65	7.29
	>50,000		N/A											
HL3M	≤25,000	0.98	9.50	2.51	0.97	0.26	2.22	-2.00	0.11	**0.99**	10.54	3.61	10.44	4.27
	>25,000 to ≤ 50,000		N/A											
	>50,000		N/A											
HL4	≤25,000	0.85	8.95	1.31	0.80	0.15	2.18	-13.45	0.11	**0.87**	9.55	6.42	9.49	8.15
	>25,000 to ≤ 50,000	0.79	6.75	0.82	0.77	0.12	1.90	-21.72	0.15	**0.87**	7.12	7.95	7.10	9.91
	>50,000		N/A											
HL8	≤25,000	0.89	7.14	1.29	0.88	0.18	1.95	-7.06	0.14	**0.90**	7.69	5.37	7.66	6.48
	>25,000 to ≤ 50,000	0.81	5.69	0.74	0.79	0.13	1.73	-17.26	0.18	**0.87**	6.04	6.88	6.00	9.28
	>50,000		N/A											
Superpave (SP 12.5 FC2)	≤25,000	0.64	16.20	1.23	0.64	0.08	2.78	-62.54	0.06	**0.75**	16.72	13.76	16.73	16.24
	>25,000 to ≤ 50,000	0.74	14.72	2.36	0.73	0.16	2.68	-9.97	0.07	**0.80**	15.81	5.41	15.69	7.36
	>50,000	0.87	12.64	6.04	**0.94**	0.45	2.43	0.70	0.08	0.90	14.48	2.10	14.27	2.21

A similar scenario is observed for the distribution of time to maintenance, which is estimated by the PCI based on the M-E approach. From Table 8.8, Weibull distribution is found as the 'best fit' distribution for most of the categories. However, the normal distribution is also found as 'best -fit' for DFC with AADT ≤25,000, HL1 with AADT ≤25,000 and HL3 with AADT ≤25,000. In this case, neither exponential distribution nor log-normal distribution is found as 'best-fit' distribution for any of the categories. Even though there are some exceptions, the Weibull distribution is followed in the next step while estimating the probability of failure for all categories in a consistent way and also for simplicity of application. Moreover, the Weibull distribution is considered as flexible and it is commonly used to model time to failure of any component (Benjamin 1970, and Ang 1975).

Based on the distribution parameters listed in Table 8.7 and Table 8.8, the probability of failure is estimated for each category. Table 8.9 and 8.10 present the summary of the probability of failure for each for 5-year interval up to the 30th year. In both cases, the survival probability up to the fifth year is approximately 80% to 90% for each category. Corresponding probability of failure of up to the fifth year is found as 0% to 13% for field-evaluated PCI and 0% to 16.8% for MEPDG-based PCI. Therefore, this probability indicates the minimum requirement of maintenance up to first 5th year after the treatment. For field-evaluated PCI up to 10th year after treatment, a higher probability of failure is found for the case DFC with >50,000 AADT (38.8%), HL3 with AADT 25,000 to ≤50,000 (72.2%), HL3M with AADT ≤25,000 (40.4%), HL4 with AADT ≤25,000 (75.3%), HL4 with AADT 25,000 to ≤50,000 (100%), HL8 with AADT ≤25,000 (100%) and HL8 with AADT 25,000 to ≤50,000 (100%). Since the estimated mean maintenance time is less than 10 years for HL3 with AADT 25,000 to ≤50,000 (9 years), HL4 with AADT ≤25,000 (9 years), HL4 with AADT 25,000 to ≤50,000 (6.6 years), HL8 with AADT ≤25,000 (7 years) and HL8 with AADT 25,000 to ≤50,000 (6.37 years), it may have higher probability of failure. A similar scenario is found for the probability of failure up to the tenth year in the case of M-E based PCI. For both cases, the probability of failure is found as 67% to 100%, 85% to 100% and 95% to 100%, up to the 20th , 25th and 30th year respectively. The probability of failure depending on the pavement age will help pavement engineers set a priority of the road sections for next period of maintenance.

8.6 Probabilistic Approach for Determining Failure of Individual Distress

The time to maintenance is estimated based on the overall condition in terms of PCI. In the deterministic approach, the time to maintenance is estimated by the deterioration equation when the trigger value becomes 65 or less (refer to section 8.4). In the probabilistic approach, the probability of failure is also estimated from the distribution of the mean time to maintenance. The mean time to maintenance is calculated from the overall condition of pavement in terms of PCI when the trigger value becomes 65 or less (refer to section 8.5). In previous sections, the time to maintenance mainly focuses on the overall condition of the pavement. However, the pavement may expect failure due to any specific distress (if the target value of failure is reached for any individual distress) before reaching the PCI trigger value of failure. For this reason, the probability of failure of each specific distress is investigated along with the overall condition of the pavement.

Table 8.9: Probability of Failure for PCI based on Field-evaluated Value

Surface Material Type	AADT	Mean Time to Maintenance from Distribution of Field-evaluated PCI model (Year)	Parameter of Weibull Distribution		Probability of Failure						
			Shape Parameterr, α	Scale Parameter, β	Survival Probability up to 5th Year	Probability of Failure up to 5th Year	Probability of Failure up to 10th Year	Probability of Failure up to 15th Year	Probability of Failure up to 20th Year	Probability of Failure up to 25th Year	Probability of Failure up to 30th Year
DFC	≤25,000	17.02	2.52	19.18	0.97	0.03	0.18	0.42	0.67	0.86	0.95
	>25,000 to ≤ 50,000	14.02	5.65	15.17	1.00	0.00	0.09	0.61	0.99	1.00	1.00
	>50,000	13.23	1.79	14.87	0.87	0.13	**0.39**	0.64	0.82	0.92	0.97
HL1	≤25,000	13.71	3.25	15.29	0.97	0.03	0.22	0.61	0.91	0.99	1.00
	>25,000 to ≤ 50,000	12.95	5.20	14.07	1.00	0.01	0.16	0.75	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL3	≤25,000	13.17	2.67	14.82	0.95	0.05	0.30	0.64	0.89	0.98	1.00
	>25,000 to ≤ 50,000	9.02	6.86	9.65	0.99	0.01	**0.72**	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL3M	≤25,000	10.80	3.66	11.97	0.96	0.04	**0.40**	0.90	1.00	1.00	1.00
	>25,000 to ≤ 50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL4	≤25,000	9.09	8.62	9.62	1.00	0.00	**0.75**	1.00	1.00	1.00	1.00
	>25,000 to ≤ 50,000	6.66	9.93	7.00	0.97	0.04	**1.00**	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL8	≤25,000	7.05	9.37	7.43	0.98	0.02	**1.00**	1.00	1.00	1.00	1.00
	>25,000 to ≤ 50,000	6.37	8.52	6.75	0.93	0.08	**1.00**	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Superpave(SP 12.5 FC2)	≤25,000	16.82	12.79	17.51	1.00	0.00	0.00	0.13	1.00	1.00	1.00
	>25,000 to ≤ 50,000	15.86	6.20	17.07	1.00	0.00	0.04	0.36	0.93	1.00	1.00
	>50,000	14.16	1.95	15.97	0.90	0.10	0.33	0.59	0.79	0.91	0.97

Table 8.10: Probability of Failure for PCI based on M-E Approach

Surface Material Type	AADT	Mean Time to Maintenance from Distribution of MEPDG-based PCI Model (Years)	Parameter of Weibull Distribution		Probability of Failure						
			Shape Parameterr α	Scale Parameter, β	Survival Prob. Up to 5th Year	Up to 5th Year	Up to 10th Year	Up to 15th Year	Up to 20th Year	Up to 25th Year	Up to 30th Year
DFC	≤25,000	14.92	2.53	16.81	0.96	0.05	0.24	0.53	0.79	0.94	0.99
	>25,000 to ≤ 50,000	12.25	5.24	13.31	0.99	0.01	0.20	0.85	1.00	1.00	1.00
	>50,000	9.13	2.37	10.31	0.84	0.17	0.61	0.91	0.99	1.00	1.00
HL1	≤25,000	16.40	2.31	18.51	0.95	0.05	0.22	0.46	0.70	0.87	0.95
	>25,000 to ≤ 50,000	13.05	4.51	14.30	0.99	0.01	0.18	0.71	0.99	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL3	≤25,000	10.68	5.03	11.63	0.99	0.01	0.37	0.97	1.00	1.00	1.00
	>25,000 to ≤ 50,000	9.05	7.29	9.65	0.99	0.01	0.73	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL3M	≤25,000	9.50	4.27	10.44	0.96	0.04	0.57	1.00	1.00	1.00	1.00
	>25,000 to ≤ 50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL4	≤25,000	8.95	8.15	9.49	1.00	0.01	0.78	1.00	1.00	1.00	1.00
	>25,000 to ≤ 50,000	6.75	9.91	7.10	0.97	0.03	1.00	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
HL8	≤25,000	7.14	6.48	7.66	0.94	0.06	1.00	1.00	1.00	1.00	1.00
	>25,000 to ≤ 50,000	5.69	9.28	6.00	0.83	0.17	1.00	1.00	1.00	1.00	1.00
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Superpave (SP 12.5 FC2)	≤25,000	16.20	16.24	16.73	1.00	0.00	0.00	0.16	1.00	1.00	1.00
	>25,000 to ≤ 50,000	14.72	7.36	15.69	1.00	0.00	0.04	0.51	1.00	1.00	1.00
	>50,000	12.64	2.21	14.27	0.91	0.09	0.37	0.67	0.88	0.97	0.99

Table 8.11: Probability of Failure and Maintenance due to Failure in Individual Distress

Surface Material	AADT	Probability of Failure					Probability of Maintenance due to Failure in Individual Distress
		Bottom-up Fatigue Cracking	Top-down Fatigue Cracking	Thermal Cracking	Rut Depth	IRI	
DFC	≤25,000	0.000	0.000	0.000	0.000	0.000	0.000
	>25,000 to ≤ 50,000	0.000	0.001	0.000	0.000	0.000	0.001
	>50,000	0.000	0.001	0.005	0.000	0.004	0.005
HL1	≤25,000	0.000	0.000	0.000	0.002	0.001	0.002
	>25,000 to ≤ 50,000	0.000	0.000	0.000	0.002	0.008	0.008
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A
HL3	≤25,000	0.000	0.000	0.010	0.000	0.001	0.010
	>25,000 to ≤ 50,000	0.000	0.000	0.031	0.000	0.015	0.031
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A
HL3M	≤25,000	0.000	0.000	0.002	0.000	0.003	0.003
	>25,000 to ≤ 50,000	N/A	N/A	N/A	N/A	N/A	N/A
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A
HL4	≤25,000	0.000	0.000	0.015	0.001	0.000	0.015
	>25,000 to ≤ 50,000	0.000	0.000	0.020	0.006	0.000	0.020
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A
HL8	≤25,000	0.000	0.000	0.000	0.000	0.000	0.000
	>25,000 to ≤ 50,000	0.000	0.000	0.000	0.004	0.000	0.004
	>50,000	N/A	N/A	N/A	N/A	N/A	N/A
Superpave (SP 12.5 FC2)	≤25,000	0.000	0.000	0.000	0.007	0.029	0.029
	>25,000 to ≤ 50,000	0.000	0.000	0.000	0.008	0.041	0.041
	>50,000	0.000	0.000	0.000	0.041	0.062	0.062

At first, the distribution of each individual distress is investigated. The distribution of IRI, permanent deformation, thermal cracking, bottom-up fatigue cracking, top-down fatigue cracking, along with the distribution of DMI and PCI, are observed for years for the selected road sections. For each road section, the yearly performance in terms of the condition of each individual distress is observed. A Monte Carlo simulation is carried out by considering the distribution parameters for each category of materials and traffic levels. The probability of failure of each individual distress is estimated for the corresponding threshold value of failure.

The time to maintenance is triggered if there is any failure of any specific distress over the performance cycle regardless of the PCI value. Table 8.11 summarizes the probability of failure considering each category of distress separately.

From Table 8.11, it is found that the probability of failure for individual distress is very low (less than 10% for each category) over the performance cycle. The resultant probability of maintenance is also very low (less than 10%) for each category.

This analysis will help pavement engineers make decisions regarding the selection of treatment in terms of the surface layer. The estimation of the probability of failure for surface layer types for specific traffic groups and corresponding time to maintenance will help pavement management decide on effective maintenance strategies.

8.7 Chapter Summary

In this chapter, an overall condition index model is estimated by incorporating the distresses of the M-E approach. The experimental design consists of a total of 128 highway sections which contain both Marshall mixes and Superpave mixes. The model of the overall condition is developed based on both the M-E approach and field-evaluated performance. The maintenance time requirement is estimated by the deterministic approach and corresponding probability of failure is estimated by the probabilistic approach.

The selected highway sections are found with high-traffic volume (category 'E') and thus are further categorized into three groups based on the distribution of the AADT. For this reason, the deterioration models are estimated for the three groups to recognize the influence on the models due to their differences in AADT. The performance predicted by the model is comparable to the actual field-evaluated PCI. The improvement in PCI with the overlay design with Superpave and DFC are higher compared to other HL surfaces.

In the deterministic approach, the expected time to maintenance for the overlay with DFC and Superpave is higher than hot-laid layers. On the other hand, HL-8 requires early maintenance compared to other types of overlay layers. The traffic level for the same surface layer affects the required time to maintenance.

The AADT affects the required time to maintenance from 15 to 9 years in DFC for low AADT to high AADT. For the road sections with Superpave mixes, the required time to maintenance varies from 16 to 13 years for low AADT to high AADT. HL-8 requires early maintenance (6 to 7 years) than other types. It is also found that the estimated time to maintenance for most categories, except HL1 with AADT $\leq$25,000, in the M-E approach is equal or lower than the field-evaluated PCI. This may happen as the distresses predicted by the M-E approach are over-predicted in most cases.

Since the distribution of time to failure or maintenance may vary depending on the types of materials and traffic, these distributions are further investigated. It is found that the Weibull distribution is the best fit for most of the categories of traffic and materials. In the probabilistic approach, the probability of failure is estimated for each category. The probability of failure for each 5-year interval up to the 30th year is investigated. In both cases of field-evaluated PCI and the M-E approach, the survival probability up to the 5th year is approximately 80% to 90% for each category. The corresponding probability of failure up to the 5th year is very low, with 0% to 13% for field-evaluated PCI and 0% to 16.8% for MEPDG-based PCI. Therefore, this probability indicates the minimum requirement of maintenance up to the first 5th year after the treatment. For field-evaluated PCI up to 10th year after treatment, a higher probability of failure is found for the case DFC with >50,000 AADT (38.8%), HL3 with AADT 25,000 to ≤50,000 (72.2%), HL3M with AADT ≤25,000 (40.4%), HL4 with AADT ≤25,000 (75.3%), HL4 with AADT 25,000 to ≤50,000 (100%), HL8 with AADT ≤25,000 (100%) and HL8 with AADT 25,000 to ≤50,000 (100%). A similar scenario is found for the probability of failure up to the tenth year in the case of the M-E based PCI. Moreover, for all categories, the probability of failure up to the 20th, 25th and 30th year are very high. This probability of failure depending on the pavement age will help pavement engineers set a prioritized maintenance schedule for the road sections.

The time to maintenance is estimated using both the deterministic and probability of failure is estimated by a probabilistic approach based on the overall condition in terms of PCI. However, the pavement may expect failure due to any specific distress (if the target value of failure is reached for any individual distress) before reaching the PCI trigger value of maintenance. For this reason, the probability of failure of each specific distress is investigated as well. For this purpose, a Monte Carlo simulation is carried out by considering the distribution parameters for each category of materials and traffic levels. The distresses considered for this investigations are IRI, permanent deformation, thermal cracking, bottom-up fatigue cracking and top-down fatigue cracking. The probability of failure of each individual distress is estimated for the corresponding threshold value of failure. From the Monte Carlo simulation, it is found that the probability of failure for individual distress is very low (less than 10% for each category) over the performance cycle. The resultant probability of maintenance is also very low (less than 10%) for each category.

This analysis will help pavement engineers to make a decision in selecting treatment in terms of the surface layer. The estimation of the probability of failure for surface layer types for specific traffic groups and corresponding time to maintenance will help select priority lists of road sections for maintenance and enable management to decide on effective maintenance strategies. The results from the investigations can be used for predicting the future pavement conditions for different levels of traffic and materials and thereby can be used in M&R decisions in a realistic way.

CHAPTER 9
INVESTIGATING LIFE CYCLE COST ANALYSIS

In this chapter, an LCCA is carried out for a period of forty years for alternate resurfacing options based on the deterioration models of the overall condition that are developed in the previous chapter.

The work of this chapter was presented at the TAC Conference 2016 (Jannat 2016).

9.1 Introduction

Transportation agencies spend billions of dollars on infrastructure asset management every year. Identification of cost-effective practices to preserve this huge investment made in the highway infrastructure is always challenging for highway agencies. A cost-effective pavement M&R approach is needed to allocate the transportation infrastructure budget in an efficient way.

Recent research (Mandapaka 2012, De la Graza 2010, and Labi 2005) has contributed significantly to investigating LCCA to identify the cost-effective pavement M&R schedules that are developed generally based on a subjective index or M&R decision trees. However, the prediction of pavement performance is improved by incorporating the effect of traffic and materials which is investigated in the previous chapter. Therefore, this improved prediction of pavement performance will ensure more precise identification of the cost-effective M&R strategy in a LCCA.

This chapter will analyse the LCCA of pavement considering the overall condition of the pavement and the deterioration model of the performance index based on specific materials and traffic level which are developed in the previous chapter.

9.2 Investigation of LCCA

This chapter will investigate the LCCA of pavement by considering the estimated PCI deterioration model developed in the previous chapter both for (i) field-evaluated PCI, and (ii) PCI by the M-E approach.

The deterioration rate of the overall condition is found to change depending on the type of materials and AADT level. This variation of deterioration is taken into account for predicting future performance and remaining service life. The LCCA is carried out by considering the variation of deterioration for materials and traffic volume investigated in the previous chapter. In this study, the LCCA is carried out for period of 40 years. The LCCA is carried out by predicting future performance for the type of treatment applied. It is imperative to predict the deterioration of pavement in a precise way by considering material properties and traffic levels. The steps utilized in investigating the LCCA are presented in Figure 9.1.

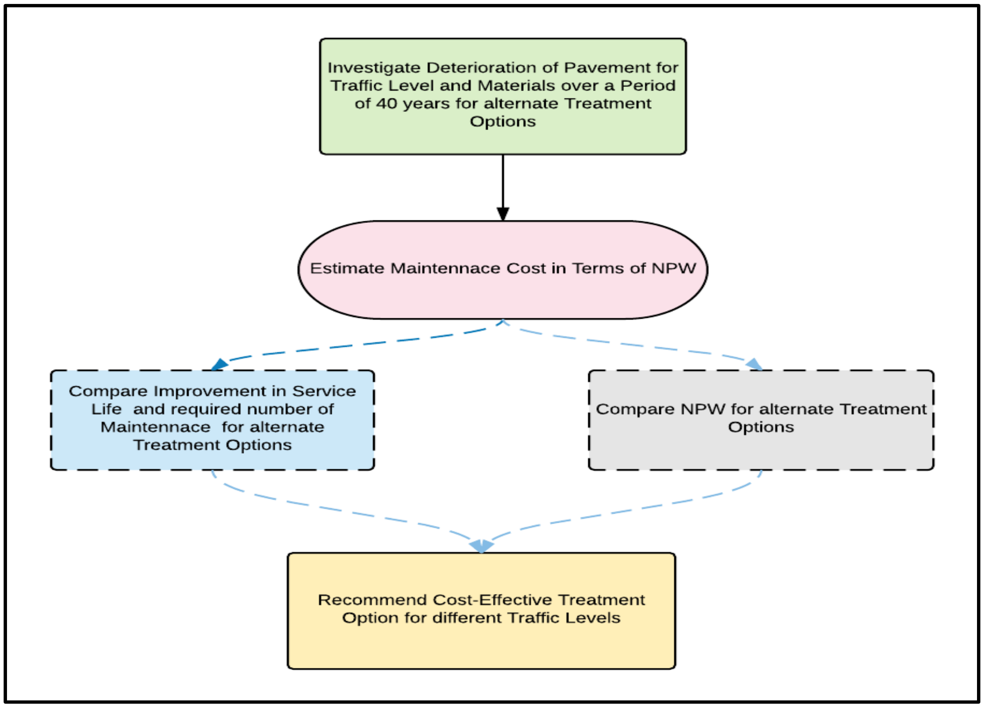


Figure 9.1: Steps in Investigation of LCCA

Since the deterioration of the overall condition has a variation on the road segment and is dependent on AC layer types and AADT levels, it will impact the maintenance decisions and scheduling. For this reason, a LCCA is carried out by considering this variation due to types of pavement layers and AADT levels. In this study, the variation of layer thickness is not taken into consideration as layer thickness was not found to vary on a large scale. Unit costs of materials used in this study are shown in Table 9.1.

For empirical investigations, a typical pavement structure is considered, which consists of a one kilometer length section with three lanes in each direction (average 3.65m width for each lane). A sample cost estimation for a typical pavement structure is shown in Table 9.2.

Net present worth (NPW) is compared for each alternative overlay layer for a period of 40 years. NPW is calculated in the following equation (TAC 2013):

$$NPW = IC + \sum_{i=1}^{k} M\&R_j \left(\frac{1}{1+i_{discount}}\right)^{n_j} - sv\left(\frac{1}{1+i_{discount}}\right)^{AP} \tag{9.1}$$

Where,
NPW= Net Present Worth ($)
IC= Initial Cost ($)
k= Number of future maintenance, preservation and rehabilitation activities
$M\&R_j$ = Cost of j^{th} future maintenance, preservation and rehabilitation activities ($)
$i_{discount}$ = Discount Rate (%)

n_j= Number of years from the present of the j^{th} future maintenance, preservation or rehabilitation treatments
SV= Salvage Value ($)
AP= Analysis period (year)

In this study, a discount rate of 5% is used and the salvage value is not taken into consideration. The PCI value is considered as a trigger level for maintenance when it becomes 65 or less. The improvement in performance and associated service life is observed for all resurfacing options.

On the selected pavement section, the overall performance in terms of deterioration of PCI is observed. If the PCI value becomes 65 or less, a treatment is applied from following six options (which are mainly available in the database for the selected road sections):

- Overlay with DFC
- Overlay with HL-1
- Overlay with HL-3
- Overlay with HL-4
- Overlay with HL-8
- Overlay with Superpave

The maintenance activities (rout and seal) are also applied every three years over the 40 years. The predicted service life for each overlay option is different for the selected category of traffic and materials. For this reason, the required time to apply the treatment is different and the required number of treatments are found to vary in a different way. Figure 9.2 and Figure 9.3 show the variation of performance of the pavement section (with existing DFC with AADT <25,000) for alternate treatment options.

The activities that are taken in the LCCA for PCI model based on the field-evaluated value and the PCI model based on the M-E approach are listed in Table 9.3 and Table 9.4, respectively. The NPW values are compared to identify the cost-effective treatment option. The NPW values for field-evaluated PCI model and for PCI based on M-E approach are presented in Table 9.5 and Table 9.6 respectively.

9.3 Discussion of Results

As one would expect from the variation in pavement deterioration, certain materials are more appropriate than others. However, the unit price and thickness might have a significant impact on LCCA too. With the LCCA, the existing pavement surface is considered for overlay when it is required and an alternate resurface layers is selected from the Superpave, DFC, HL1, HL3, HL4, and HL8.

From Table 9.1 it is observed that the unit costs of pavement materials increased by about 70% from the year 1997 to 2010. The base year 2010 is considered in this study to calculate the NPW. As the performance records are taken in this study are mostly up to the year 2010. However, the NPW value considers the discounted price accordingly.

Table 9.2 shows sample cost estimates of each overlay layer that are used in the study. It is observed that unit cost ($/ton) of HL-4 and Superpave is higher than the other AC layers. However, the total cost may vary depending on the required number of application of the treatment options for each category.

The activities that are taken in the LCCA for the PCI model based on the field-evaluated value and the PCI model based on the M-E approach are listed in Table 9.3 and Table 9.4. It is observed that required number of treatments are higher if the pavement is resurfaced with HL-4, and HL-8. The opposite scenario is observed in the case of DFC, Superpave, HL-1 and HL-3.

Figure 9.2 and Figure 9.3 show the variation of performance of the pavement section (with existing DFC with AADT <25,000) for alternate treatment options. It is observed that the rate of deterioration varies at a higher rate in case of HL-4, and HL-8 than other layers.

The improvement in PCI is also different for the respect treatment type. The overall comparison of all treatments is shown in Figure 9.3 which presents all these variations in one frame.

From Table 9.5, a comparison of NPW values among alternative treatment options reveals that the resurfacing of pavement with DFC and HL1 are more cost-effective than other resurfacing options. For AADT ≤25,000, resurfacing with HL1 is found as the most cost-effective treatment option. However, for AADT >25,000 to ≤ 50,000 resurfacing with DFC and HL1 is found as the cost-effective treatment option. For AADT>50,000, resurfacing with DFC is found as the cost-effective treatment option.

From Table 9.6, similar scenario is found. DFC is found as cost-effective resurface option for AADT>50,000. Resurfacing with HL-1 is found as cost –effective treatment option when AADT ≤25,000 and >25,000 to ≤ 50,000.

9.4 Chapter Summary

This study investigates LCCA by considering the overall condition of pavement in terms of PCI, which is estimated from both field-evaluated and MEPDG-based predicted distress cases. The deterioration patterns of PCI are found to vary depending on the type of materials and AADT levels.

A comparison of NPW values among the alternative treatment options reveals that the resurfacing of pavement with DFC and HL1 are more cost-effective than other alternative options.

Resurfacing with HL1 is the cost-effective treatment option for highway sections with AADT ≤25,000. Resurfacing with DFC is the cost-effective treatment option for highways with AADT >50,000. Resurfacing with HL-1 and DFC are found as the cost-effective treatment option for highways with AADT >25,000 to ≤ 50,000. Resurfacing with Superpave is also found as the cost-effective option when the existing pavement is with Superpave for AADT >50,000.

Table 9.1: Costs of Materials

Surface Material	Quantity (Tonnes)	Average Costs in 1997 ($)	Standard Deviation in 1997	Discounted Average Costs ($) as of 2010
Granual A	0 -1000	27.89	14.20	47.70
	1000 - 10000	14.40	3.80	24.63
	10000 -100000	10.79	2.50	18.45
	100000+	9.22	1.90	15.77
Granual B	0 -1000	10.29	2.90	17.60
	1000 - 10000	8.98	2.50	15.36
	10000 -100000	7.16	1.90	12.25
	100000+	5.58	1.30	9.54
HL1	0-1000	97.12	45.20	166.11
	1000-10000	58.96	10.60	100.84
	10000+	46.49	4.50	79.51
HL3	0-1000	140.15	120.30	239.70
	1000-10000	74.89	48.00	128.09
	10000 - 100000	87.70	73.10	150.00
	100000+	46.83	8.90	80.10
HL4	0-1000	118.31	56.27	202.35
	1000-10000	109.35	53.00	187.03
	10000 - 100000	56.50	18.80	96.63
	100000+	43.62	7.50	74.61
HL8	100-1000	62.90	18.00	107.58
	1000-5000	45.17	6.01	77.26
	5000+	38.18	4.00	65.30
HDBC	0-1000	69.08	15.40	118.15
	1000-5000	51.14	11.70	87.47
	5000+	43.73	6.60	74.79
DFC	0-1000	85.94	27.30	146.99
	1000-5000	65.57	9.30	112.15
	5000+	59.32	9.40	101.46
Cold In Place Recycled Mix	10000+	4.00	1.10	6.84
Rout and Seal	100-1000	7.24	2.80	12.38
	1000-15000	4.27	4.60	7.30
	100000+	1.10	0.20	1.88
Removal Asphalt Partial Depth	0-1000	10.82	5.10	18.51
	1000-10000	4.10	2.30	7.01
	10000-100000	2.00	1.20	3.42
	100000+	1.19	0.40	2.04
Rout and Seal	m			2.25
SuperPave 12.5 FC2	t			142.47

Table 9.2: Sample Cost Estimation of Different Pavement Layers

Activity	Thickness (mm)	Length (m)	Width (m)	No. of Lanes	Area (m^2)	Volume (m^3)	Unit Weight (t/m3)	Total Quantity (ton)	Cost/Unit ($/t)	Activity Cost ($)
DFC	40	1000	3.65	3	10,950	438	2.4	1,051	112.15	117,889
HL1	40	1000	3.65	3	10,950	438	2.4	1,051	100.84	106,005
HL3	40	1000	3.65	3	10,950	438	2.4	1,051	128.09	134,645
HL4	40	1000	3.65	3	10,950	438	2.4	1,051	187.03	196,601
HL8	58	1000	3.65	3	10,950	635	2.4	1,524	77.26	117,757
Superpave (SP 12.5 FC2)	40	1000	3.65	3	10,950	438	2.4	1,051	142.47	149,765
Rout and Seal		1000							2.25	2,250
Granular A - 150 mm	150	1000	3.65	3	10,950	1,643	2.2	3,614	24.63	88,997
Granular B - 450 mm	450	1000	3.65	3	10,950	4,928	2.2	10,841	12.25	132,753

With the results of LCCA, pavement engineers will be able to identify cost-effective treatment options. Since this study considers the effect of materials and traffic, this approach is considered more reliable for specific pavement types. Moreover, the variation of deterioration due to traffic and materials are considered into the LCCA, which provides more reliable analysis. This investigation will enable management to decide on maintenance strategies by selecting cost-effective maintenance options for an effective PM

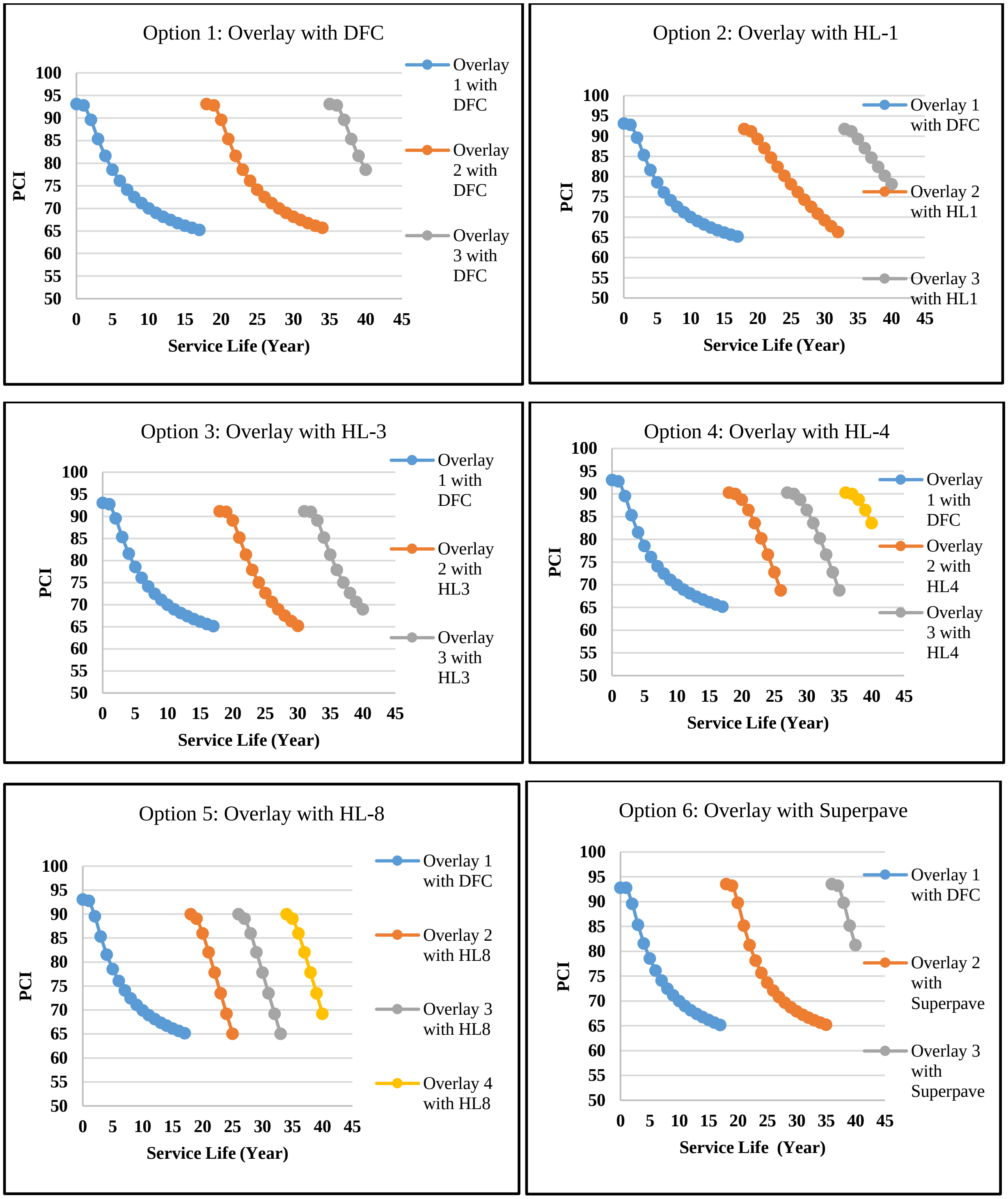


Figure 9.2: Performance Cycle of a Pavement Section with DFC (AADT <25,000) for alternate Overlay Option

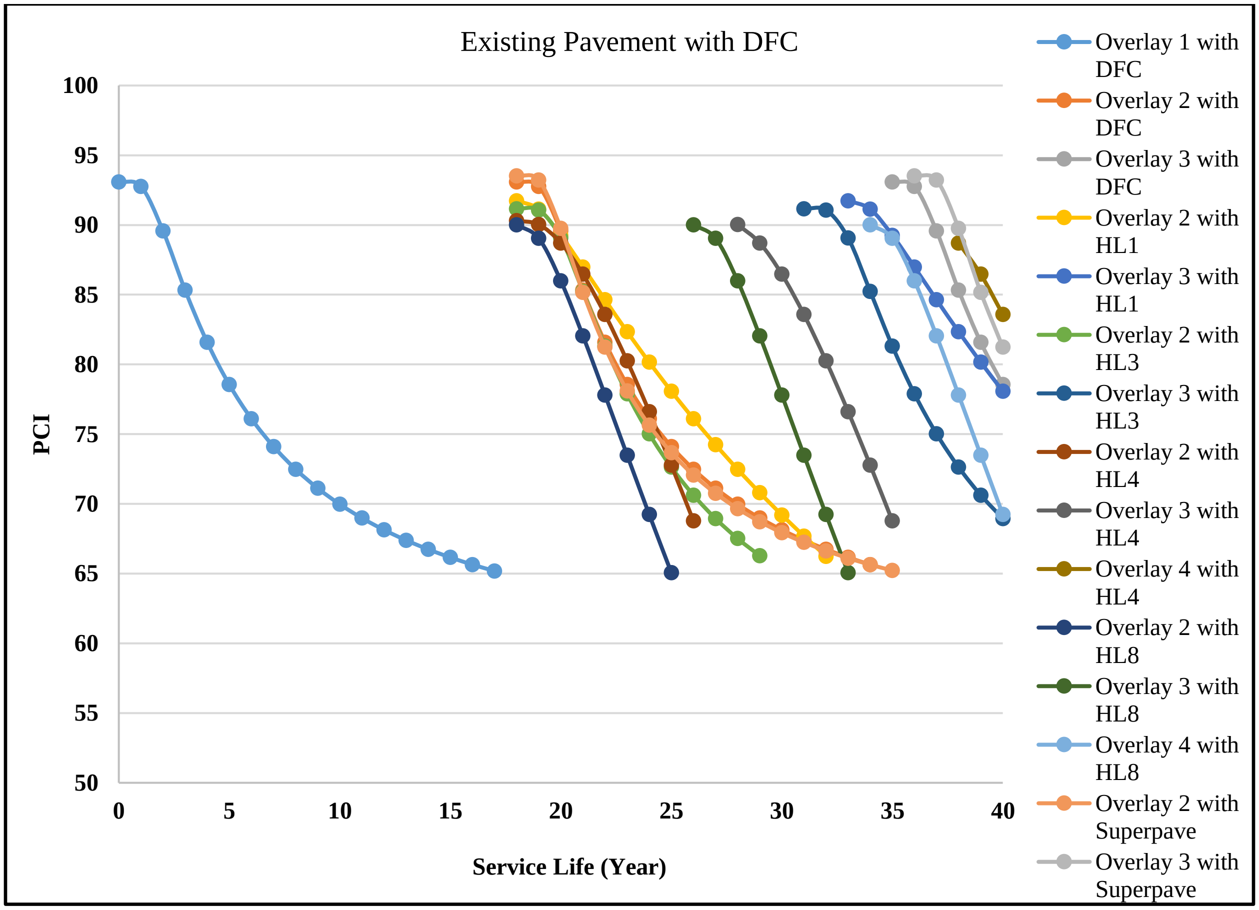


Figure 9.3: Performance Cycles for alternate Overlay Options over a Pavement Section with DFC (AADT <25,000)

Table 9.3: Summary of Activities in LCCA Using PCI Model based on Field-Evaluated Value

Existing Surface	**AADT**	**Activity**					
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**
DFC	≤25,000	DFC on 18th year and 35th year along with Rout& Seal on each 3rd year	HL1 on 18th & 24th year along with Rout & Seal on each 3rd year	HL3 on 18th and 31st year along with Rout & Seal on each 3rd year	HL4 on 18th, 27th & 36th year along with Rout & Seal on each 3rd year	HL8 on 18th, 26th & 34th year along with Rout & Seal on each3rd year	Superpave on 18th, & 36th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 16th year and 32nd year along with Rout& Seal on each 3rd year	HL1 on 16th & 33rd year along with Rout & Seal on each 3rd year	HL3 on 16th and 29th year along with Rout & Seal on each 3rd year	HL4 on 16th, ,24th, 32nd & 40h year along with Rout & Seal on each 3rd year	HL8 on 16th, 23rd, 30th & 37th year along with Rout & Seal on each3rd year	Superpave on 16th, & 34th year along with Rout & Seal on each3rd year
	>50,000	DFC on 13th year and 29th year along with Rout& Seal on each 3rd year					Superpave on 13th, & 28th year along with Rout & Seal on each3rd year
HL1	≤25,000	DFC on 15th year and 33rd year along with Rout& Seal on each 3rd year	HL1 on 15th & 30th year along with Rout & Seal on each 3rd year	HL3 on 15th and 28th year along with Rout & Seal on each 3rd year	HL4 on 15th, 24th & 33rd year along with Rout & Seal on each 3rd year	HL8 on 15th, 23rd, 31st & 39th year along with Rout & Seal on each3rd year	Superpave on 15th, & 33rd year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 14th year and 30th year along with Rout& Seal on each 3rd year	HL1 on 14th & 28th year along with Rout & Seal on each 3rd year	HL3 on 14th, 24th and 34th year along with Rout & Seal on each 3rd year	HL4 on 14th, 22nd, 30th & 38th year along with Rout & Seal on each 3rd year	HL8 on 14th, 21st, 28th & 35th year along with Rout & Seal on each3rd year	Superpave on 14th, & 32nd year along with Rout & Seal on each3rd year
HL3	≤25,000	DFC on 13th year and 31st year along with Rout& Seal on each 3rd year	HL1 on 13th & 27th year along with Rout & Seal on each 3rd year	HL3 on 13th,26th and 39th year along with Rout & Seal on each 3rd year	HL4 on 13th, 22nd, 31st & 40th year along with Rout & Seal on each 3rd year	HL8 on 13th, 21st, 29th, & 37th year along with Rout & Seal on each3rd year	Superpave on 13th, & 30th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 10th year and 26th year along with Rout& Seal on each 3rd year	HL1 on 10th, 24th& 38th year along with Rout & Seal on each 3rd year	HL3 on 10th, 20th, and 30th year along with Rout & Seal on each 3rd year	HL4 on 10th, 18th, 26th & 34th year along with Rout & Seal on each 3rd year	HL8 on 10th, 17th, 24th,31st, & 38th year along with Rout & Seal on each3rd year	Superpave on 10th, & 28th year along with Rout & Seal on each3rd year

Existing Surface	AADT	Activity					
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**
HL4	≤25,000	DFC on 9th year and 27th year along with Rout& Seal on each 3rd year	HL1 on 9th, 24th,& 39th year along with Rout & Seal on each 3rd year	HL3 on 9th, 22nd & 35th year along with Rout & Seal on each 3rd year	HL4 on 9th, 18th, 27th & 36th year along with Rout & Seal on each 3rd year	HL8 on 13th, 21st, 29th, & 37th year along with Rout & Seal on each 3rd year	Superpave on 13th, & 30th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 8th, 24th, and 40th year along with Rout & Seal on each 3rd year	HL1 on 8th, 22nd, & 36th year along with Rout & Seal on each 3rd year	HL3 on 18th and 31st year along with Rout & Seal on each 3rd year	HL4 on 8th, 18th, 28th, & 38th year along with Rout & Seal on each 3rd year	HL8 on 8th, 15th, 22nd, 29th & 36th year along with Rout & Seal on each3rd year	Superpave on 8th, & 26th year along with Rout & Seal on each3rd year
HL8	≤25,000	DFC on 8th year and 26th year along with Rout& Seal on each 3rd year	HL1 on 8th, 23rd, & 38th year along with Rout & Seal on each 3rd year	HL3 on 8th, 21st, and 35th year along with Rout & Seal on each 3rd year	HL4 on 8th, 17th, 26th & 35th year along with Rout & Seal on each 3rd year	HL8 on 8th, 21st, & 34th year along with Rout & Seal on each3rd year	Superpave on 8th, & 26th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 7th, 23rd, and 40th year along with Rout& Seal on each 3rd year	HL1 on 7th, 21st, & 36th year along with Rout & Seal on each 3rd year	HL3 on 7th, 17th, 27th, and 37th year along with Rout & Seal on each 3rd year	HL4 on 7th, 15th, 23rd, 31st and 39th year along with Rout & Seal on each 3rd year	HL8 on 7th, 14th, 21st, & 35th year along with Rout & Seal on each3rd year	Superpave on 7th & 25th year along with Rout & Seal on each3rd year
Superpave	≤25,000	DFC on 18th & 36th year along with Rout& Seal on each 3rd year	HL1 on 18th, & 33rd year along with Rout & Seal on each 3rd year	HL3 on 18th and 31st year along with Rout & Seal on each 3rd year	HL4 on 18th, 27th & 36th year along with Rout & Seal on each 3rd year	HL8 on 18th, 26th, & 34th year along with Rout & Seal on each3rd year	Superpave on 18th & 36th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 17th & 33rd year along with Rout& Seal on each 3rd year	HL1 on 17th, & 31st year along with Rout & Seal on each 3rd year	HL3 on 17th,27th, and 37th year along with Rout & Seal on each 3rd year	HL4 on 17th, 25th & 33rd year along with Rout & Seal on each 3rd year	HL8 on 17th, 24th, 31st, & 38th year along with Rout & Seal on each3rd year	Superpave on 17th & 34th year along with Rout & Seal on each3rd year
	>50,000	DFC on 15th & 31st year along with Rout& Seal on each 3rd year					Superpave on 15th & 30th year along with Rout & Seal on each3rd year

Table 9.4: Summary of Activities in LCCA Using PCI based on M-E Approach

Existing Material	AADT	Activity					
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**
DFC	≤25,000	DFC on 16th year and 32th year along with Rout& Seal on each 3rd year	HL1 on 16th & 34th year along with Rout & Seal on each 3rd year	HL3 on 16th,27th and 38th year along with Rout & Seal on each 3rd year	HL4 on 18th, 25th & 34th year along with Rout & Seal on each 3rd year	HL8 on 16th, 24th,32nd , & 40th year along with Rout & Seal on each3rd year	Superpave on 18th, & 36th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 13th year and 29th year along with Rout& Seal on each 3rd year	HL1 on 13th & 27th year along with Rout & Seal on each 3rd year	HL3 on 13th,23rd, and 33rd year along with Rout & Seal on each 3rd year	HL4 on 13th, ,24th, and 35th year along with Rout & Seal on each 3rd year	HL8 on 13th, 23rd, & 33rd year along with Rout & Seal on each3rd year	Superpave on 13th, & 30th year along with Rout & Seal on each3rd year
	>50,000	DFC on 10th, 20th & 30th year along with Rout & Seal on each 3rd year					HL3 on 10th, 24th, and 38th year along with Rout & Seal on each 3rd year
HL1	≤25,000	DFC on 18th year and 31st year along with Rout& Seal on each 3rd year	HL1 on 18th & 32nd year along with Rout & Seal on each 3rd year	HL3 on 15th and 28th year along with Rout & Seal on each 3rd year	HL4 on 15th, 24th & 33rd year along with Rout & Seal on each 3rd year	HL8 on 15th, 23rd, 31st & 39th year along with Rout & Seal on each3rd year	Superpave on 15th, & 33rd year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 14th, 27th, and 40th year along with Rout& Seal on each 3rd year	HL1 on 14th & 28th year along with Rout & Seal on each 3rd year	HL3 on 14th, 24th and 34th year along with Rout & Seal on each 3rd year	HL4 on 14th, 22nd, 30th & 38th year along with Rout & Seal on each 3rd year	HL8 on 14th, 21st, 28th & 35th year along with Rout & Seal on each3rd year	Superpave on 14th, & 31st year along with Rout & Seal on each3rd year
HL3	≤25,000	DFC on 11th & 27th year along with Rout & Seal on each 3rd year	HL1 on 11th & 28th year along with Rout & Seal on each 3rd year	HL3 on 11th, 22nd, and 33rd year along with Rout & Seal on each 3rd year	HL4 on 11th, 20th, , 29th & 38th year along with Rout & Seal on each 3rd year	HL8 on 11th, 19th, 27th, & 35th year along with Rout &	Superpave on 11th, & 28th year along with Rout & Seal on each3rd year

Existing Material	**AADT**	**Activity**					
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**
						Seal on each3rd year	
	>25,000 to ≤ 50,000	DFC on 10th, 23rd, and 36th year along with Rout& Seal on each 3rd year	HL1 on 10th, 24th, & 38th year along with Rout & Seal on each 3rd year	HL3 on 10th, 20th, and 30th year along with Rout & Seal on each 3rd year	HL4 on 10th, 18th, 26th & 34th year along with Rout & Seal on each 3rd year	HL8 on 10th, 17th, 24th,31st, & 38th year along with Rout & Seal on each3rd year	Superpave on 10th, & 27th year along with Rout & Seal on each3rd year
HL4	≤25,000	DFC on 9th year and 25th year along with Rout& Seal on each 3rd year	HL1 on 9th, 24th,& 39th year along with Rout & Seal on each 3rd year	HL3 on 9th, 20th, & 31st year along with Rout & Seal on each 3rd year	HL4 on 9th, 22nd, 31st & 40th year along with Rout & Seal on each 3rd year	HL8 on 13th, 21st, 29th, & 37th year along with Rout & Seal on each 3rd year	Superpave on 13th, & 30th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 8th, 21st, and 34th year along with Rout & Seal on each 3rd year	HL1 on 8th, 22nd, & 36th year along with Rout & Seal on each 3rd year	HL3 on 8th 18th, 28th, and 38th year along with Rout & Seal on each 3rd year	HL4 on 8th, 18th, 28th, & 38th year along with Rout & Seal on each 3rd year	HL8 on 8th, 15th, 22nd, 29th & 36th year along with Rout & Seal on each3rd year	Superpave on 8th, & 25th year along with Rout & Seal on each3rd year
HL8	≤25,000	DFC on 8th year and 26th year along with Rout& Seal on each 3rd year	HL1 on 8th, 23rd, & 38th year along with Rout & Seal on each 3rd year	HL3 on 8th, 21st, and 35th year along with Rout & Seal on each 3rd year	HL4 on 8th, 17th, 26th & 35th year along with Rout & Seal on each 3rd year	HL8 on 8th, 21st, & 34th year along with Rout & Seal on each3rd year	Superpave on 8th, & 26th year along with Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 7th, 20th, and 33rd year along with Rout& Seal on each 3rd year	HL1 on 7th, 21st, & 36th year along with Rout & Seal on each 3rd year	HL3 on 7th, 17th, 27th, and 37th year along with Rout & Seal on each 3rd year	HL4 on 7th, 15th, 23rd, 31st and 39th year along with Rout & Seal on each 3rd year	HL8 on 7th, 14th, 21st, 28th, & 35th year along with Rout & Seal on each3rd year	Superpave on 7th & 25th year along with Rout & Seal on each3rd year
Superpave	≤25,000	DFC on 17th & 31st year along with Rout& Seal on each 3rd year	HL1 on 17th, & 35th year along with Rout	HL3 on 17th, 28th and 39th year along with	HL4 on 17th, 26th & 35th year along with	HL8 on 17th, 25th, & 33rd year along with Rout &	Superpave on 17th & 34th year along with

Existing Material	AADT	Activity					
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**
			& Seal on each 3rd year	Rout & Seal on each 3rd year	Rout & Seal on each 3rd year	Seal on each3rd year	Rout & Seal on each3rd year
	>25,000 to ≤ 50,000	DFC on 17th & 30th year along with Rout& Seal on each 3rd year	HL1 on 17th, & 31st year along with Rout & Seal on each 3rd year	HL3 on 17th,27th, and 37th year along with Rout & Seal on each 3rd year	HL4 on 17th, 25th & 33rd year along with Rout & Seal on each 3rd year	HL8 on 17th, 24th, 31st, & 38th year along with Rout & Seal on each3rd year	Superpave on 17th & 34th year along with Rout & Seal on each3rd year
	>50,000	DFC on 14th, 24th, & 34th year along with Rout& Seal on each 3rd year					Superpave on 14th & 28th year along with Rout & Seal on each3rd year

Table 9.5: Summary of NPW using PCI based on Field-evaluated Value

Existing Material	AADT	Total NPW ($)						Cost Effective Option
		Option 1: Overlay with DFC	**Option 2: Overlay with HL-1**	**Option 3: Overlay with HL-3**	**Option 4: Overlay with HL-4**	**Option 5: Overlay with HL-8**	**Option 6: Overlay with Superpave**	
DFC	≤25,000	**420,835**	**415,634**	436,411	519,347	465,378	438,549	Option 2 & 1
	>25,000 to ≤ 50,000	**429,948**	**420,578**	451,072	570,801	502,887	448,377	Option 2 & 1
	>50,000	**442,285**	N/A[13]	N/A	N/A	N/A	467,307	Option 1
HL-1	≤25,000	**418,637**	**413,814**	442,754	532,494	476,294	440,341	Option 2 & 1
	>25,000 to ≤ 50000	**425,814**	**418,690**	474,290	580,769	491,617	445,598	Option 2 & 1
HL-3	≤25,000	**455,945**	**452,026**	502,616	609,398	519,875	481,899	Option 2 & 1
	>25,000 to ≤ 50,000	**473,324**	**481,860**	532,229	662,010	588,751	497,456	Option 1& 2
HL-4	≤25,000	**535,977**	**545,023**	586,241	722,147	651,581	567,347	Option 1 & 2
	>25,000 to ≤ 50,000	**562,376**	**555,042**	631,324	724,509	654,163	572,611	Option 2& 1
HL-8	≤25000	**426,324**	**435,786**	477,361	621,766	458,211	456,863	Option 1 & 2
	>25000 to ≤ 50,000	**453,169**	**445,373**	526,721	683,643	550,382	464,697	Option 2, & 1
Superpave	≤25,000	**451,676**	**447,509**	468,287	550,029	486,600	470,424	Option 2, & 1
	>25,000 to ≤ 50,000	**457,343**	**452,409**	499,764	565,425	514,704	476,694	Option 2 &1
	>50,000	**465,206**	N/A	N/A	N/A	N/A	488,748	Option 1

[13]N/A = not available; as DFC and Superpave are used for pavement with higher traffic.

Table 9.6: Summary of NPW using PCI based on M-E Approach

Existing Material	AADT	Total NPW ($)						Cost Effective Option
		Option 1: Overlay with DFC	Option 2: Overlay with HL-1	Option 3: Overlay with HL-3	Option 4: Overlay with HL-4	Option 5: Overlay with HL-8	Option 6: Overlay with Superpave	
DFC	≤25,000	429,948	**419,870**	494,714	536,012	477,507	477,507	Option 2
	>25,000 to ≤ 50,000	442,285	**434,709**	492,465	551,786	474,825	465,216	Option 2
	>50,000	**494,993**	N/A	N/A	N/A	N/A	512,390	Option 1
HL-1	≤25,000	413,872	**383,095**	450,919	506,270	442,914	427,974	Option 2
	>25,000 to ≤ 50,000	446,833	**418,690**	474,290	580,769	491,264	447,527	Option 2
HL-3	≤25,000	467,997	**456,433**	518,893	633,430	549,673	493,181	Option 2
	>25,000 to ≤ 50,000	498,856	**481,860**	532,229	662,010	588,751	499,431	Option 2
HL-4	≤25,000	539,742	**525,168**	596,581	722,258	613,226	567,187	Option 2
	>25,000 to ≤ 50,000	573,763	**555,042**	631,324	724,509	654,163	574,768	Option 2
HL-8	≤25,000	446,986	**414,938**	488,770	621,766	458,211	479,296	Option 2
	>25,000 to ≤ 50,000	465,963	**445,373**	526,721	683,643	550,382	467,018	Option 2
Superpave	≤25,000	**457,876**	**447,974**	495,604	558,585	491,984	476,694	Option 2 & 1
	>25,000 to ≤ 50,000	**461,567**	**452,409**	499,376	565,425	515,626	476,718	Option 2 &1
	>50,000	**501,201**	N/A	N/A	N/A	N/A	**496,494**	Option 6 & 1

CHAPTER 10
CONCLUSIONS AND RECOMMENDATIONS

10.1 Conclusions

This research investigates the existing practice of using performance indices and incorporates improvements in assessing the overall performance of pavement. The objective of the research is to develop cost-effective pavement M&R strategies by incorporating the M-E approach, which overcomes the limitation of engineering judgement in assessing the overall condition of pavement.

For precise assessment of pavement conditions, this research investigates the existing variability based on current practices relevant to pavement performance evaluation and maintenance decisions. This research investigates the impact of road section lengths on overall pavement performance evaluation. The impact on maintenance decision due to changes in section lengths selected for performance evaluation is also investigated. It considers rut depth, PCI and IRI as performance indices. Since rut distribution and PCI are varied due to changes in length of road sections, maintenance decisions are also analysed by using the Monte Carlo simulation by varying the section lengths. The method of estimating the performance indices is also investigated to identify the requirements of improvement in estimation. It is found that unobserved factors influencing individual KPIs are correlated, thus the SUR method is used to estimate KPI models.

Before the application of the M-E approach, a sensitivity analysis is conducted to identify the requirements of a higher levels of accuracy of MEPDG-based software inputs. The sensitivity analysis is carried out to identify both main effects of independent input variables (such as traffic inputs: AADT, AADTT and traffic growth factors; material properties: subgrade resilient modulus, AC top-layer thickness, and milled thickness, etc.) and interaction effects of the variables (such as combination of initial permanent deformation and subgrade resilient modulus and AADTT; existing initial IRI and operational speed, etc.) on the MEPDG distresses.

Since the deterioration of pavement is affected by the traffic levels and materials types, in considering these variables, pavement deterioration model is estimated. The prediction model is developed by using a regression approach considering distresses of the M-E approach. In this study, the deterioration model is estimated for the three groups of AADT and properties of surface materials. The time to maintenance is estimated for each group of traffic level and surface material types. The time to maintenance estimated by the deterministic approach is further investigated with the probabilistic analysis to ensure that the estimate is realistic and reasonably probable.

With the increasing trend towards M&R of existing pavements, it is essential to make cost-effective use of the M&R budget. As such, identification of associated cost-effective M&R treatments is not always simple in most PMS. For this reason, a LCCA is carried out for alternate pavement treatments using the deterioration model based on traffic levels and material types.

10.2 Major Findings

From the investigations of the variability of road section length, the major findings are as follows:

- From the comparison of distribution of rut depths, it is found that most of the longer sections (10000m section) evaluate the road with low rut depth and the shorter sections (50m and 500m) detect higher rut depth. The short sections also indicate that the rut depth is relatively evenly distributed compared to longer sections. Longer sections might overlook some parts of severely damaged roads, which are in need of maintenance due to the average rut depth value over a long section.

- To avoid acceleration of pavement deterioration, the shorter sections would be more efficient compared to longer sections as they can better identify the areas where maintenance is necessary. Long sections (1000m and 10000m) in Ontario highway systems skew the outcomes of the performance measures and may cause difficulties in both treatment selection and pavement condition reporting. Thus, performance reported from long sections lengths (1000m and 10000m) are misleading when compared to the true performance of the network.

- Comparison of PCI shows the old PCI (based on the manual surveys) estimates a higher extent of defects over the shorter sections (50m and 500m) and thus gives a lower PCI value. On the other hand, over the longer sections, lower PCI values are obtained with automated surveys.
- The Monte Carlo simulation shows that 50m sections have a higher probability of maintenance requirements than 500m sections. Overall, more work is triggered if the decisions are based on shorter treatment lengths (50m and 500m), however, short treatment lengths might become difficult to manage at a network level.

From the investigation of existing estimation of performance indices, major findings are listed below:

- Unobserved factors in the PCI model are highly correlated to those in the DMI and RCI models.
- In the SUR approach, the efficiency of estimation increases with higher correlation among the random error terms of different equations. It also considers the effects of

larger sample sizes and multi-collinearity between the regressors. For this reason, efficient estimation of models with highly correlated, unobserved factors and large road networks, such as Ontario highways, require SUR approach rather than OLS approach.

From the sensitivity analysis of the MEPDG distresses, the major findings are as follows:

- Terminal IRI is sensitive to existing initial IRI, initial permanent deformation, AC air voids and AC effective binder content.
- Permanent deformation in the AC layer is sensitive to the percentage of trucks in the design lane, AC top-layer thickness, TTC types, milled thickness, initial permanent deformation and AC binder penetration grade.
- For total cracking (reflective and alligator), the sensitivity of only the AC top-layer thickness is proven to be statistically significant.
- The main effect of effective binder content, AC binder penetration grade, and AC air voids are proven to be statistically significant for AC thermal fracture.
- AC top-down fatigue cracking is found to be significantly sensitive to AC effective binder content, AC air voids, AADTT, and AC top-layer thickness. However, no sensitive input variables are found for AC bottom-up fatigue cracking for the experimental sample. Therefore, further investigation is required for AC bottom-up fatigue cracking.
- Based on these identified sensitive input variables and interaction effects, the accuracy level of major inputs of specific distresses need to be improved for precise prediction of the MEPDG-based distresses.
- Terminal IRI is sensitive to a combination of existing initial IRI- operational speed, and initial IRI-permanent deformation.
- Total permanent deformation is sensitive to the combination of initial permanent deformation –subgrade resilient modulus –AADTT.
- AC thermal cracking is sensitive to the combination of effective binder content-AADTT, and, effective binder content-AADTT-percentage of trucks in the design lane.
- AC top-down fatigue cracking is sensitive to the combination of AC air voids- initial IRI, and AC air voids-percentage of trucks in the design lane.

From the prediction of distress by the M-E analysis, the major findings are as follows:

- IRI and permanent deformation are over-predicted than those in field observations.
- Bottom-up fatigue cracking portrays an entirely different picture with under-prediction compared to field evaluation. These results show the need for local calibration of the fatigue cracking prediction models.
- Comparison of traffic level and length of service life reveals that pavement sections with higher service life of more than 14 years, forecast predicted failure in IRI, total permanent deformation, and AC permanent deformation. Failure in predicted permanent deformation is observed for the higher level of traffic regardless of the length of service life.

- A clustering regression analysis based on the surface layer confirms improved goodness of fit for both IRI and permanent deformation prediction models.
- The validation process with an independent data set confirms the validity (in terms of goodness of fit) of the calibrated models. Therefore, the predicted distresses based on the M-E approach are to be corrected further for precise prediction.

From the estimation of the overall condition index by the M-E approach, the major findings are as follows:

- The improvement in PCI of pavement with the overlay of Superpave mixes and DFC are higher than with other HL surfaces.
- In the deterministic approach, the expected time to maintenance for overlay with DFC and Superpave mixes is higher than in HL layers. On the other hand, HL-8 requires early maintenance than other types of overlay layers.
- The traffic level for same surface layer affects the required time to maintenance such as maintenance time 15 to nine years in DFC for low high to very high AADT. Similarly, it varies from 16 to 13 years in road sections with Superpave mixes for low high to very high AADT. On the other hand, HL-8 requires early maintenance (6 to 7 years) compared to other AC layer types.
- It is also found that the estimated time to maintenance for most categories (except HL1 with AADT ≤ 25,000) in the M-E approach are equal or lower than field-evaluated scenario. This may happen as the distresses predicted by the M-E approach are over-predicted in most of the categories.
- In analysing the distribution of time to failure, it is found that the 'Weibull distribution' is the best fit for most of the categories of traffic and materials.
- In the probabilistic approach, in both cases of field-evaluated PCI and the M-E approach, the survival probability up to the 5th year is approximately 80% to 90% for each category. Corresponding probability of failure of up to the 5th year is very low (0% to 13% for Field-evaluated PCI and 0% to 16.8% for MEPDG-based PCI). This probability indicates the minimum requirement of maintenance up to the 5th year after treatment.
- In case of field-evaluated PCI, a higher probability of failure is found up to 10th year after overlay (39% for DFC with AADT >50,000, 72% for HL3 with AADT 25,000 to ≤50,000, 40% for HL3M with AADT ≤25,000, 75% for HL4 with AADT ≤25,000, 100% for HL4 with AADT 25,000 to ≤50,000, 100% for HL8 with AADT ≤25,000 and 100% for HL8 with AADT 25,000 to ≤50,000). For all categories, the probability of failure up to 20th, 25th and 30th year are found as very high.
- Similar scenario is found in case of the PCI based on the M-E approach. A higher probability of failure is found up to 10th year after overlay (60% for DFC with AADT >50,000, 73% for HL3 with AADT 25,000 to ≤50,000, 57% for HL3M with AADT ≤25,000), 78% for HL4 with AADT ≤25,000, 100% for HL4 with AADT 25,000 to ≤50,000, 99.6% for HL8 with AADT ≤25,000 and 100% for HL8 with AADT 25,000 to

≤50,000). For all categories, the probability of failure up to 20th, 25th, and 30th year are found as very high.
- It is found that the probability of failure for individual distress is very low (less than 10% for each category) over the performance cycle for the estimated time to maintenance. The resultant probability of maintenance is also very low (less than 10%) for each category.

From the LCCA, major findings are as follows:

- A comparison of NPW values among the alternative treatment options reveals that the overlay of pavement with DFC and HL-1 are the most cost-effective alternative options.
- Resurfacing with HL1 is the most cost-effective treatment option for highway sections with AADT ≤25,000.
- Resurfacing with DFC is a cost-effective treatment option for highways with AADT >50,000.
- Resurfacing with HL-1 and DFC are found as the cost-effective treatment option for highways with higher AADT >25,000 to ≤ 50,000.
- Resurfacing with Superpave is also found as the cost-effective option when the existing pavement is with Superpave for AADT >50,000.

10.3 Recommendations

From the results of research investigations, major recommendations for pavement decision makers are as follows:

- Since section length in pavement evaluations significantly influence any processes that analyse the required works program. One of two recommended processes may be followed for these analytics in the PMS including:

    1. Undertake dynamic segmentation prior to the PMS analysis and verify the applicability of these section lengths in the field. These section lengths need to be reviewed on an annual basis as road conditions may change significantly from one year to another; or,
    2. Analyse fixed section length in the PMS system. For this, a section length of 500m is recommended for Ontario highways. Following the analysis, the recommended works programme is determined by rationalising the recommended treatment in order to yield practical treatment lengths and/or to combine sections into one length of similar timing and types or treatments are recommended for adjacent sections.

- Large road networks, like Ontario highways, require SUR approach rather than the OLS approach.
- Since specific sensitive properties are found for respective distresses, it will be more efficient to get higher accuracy levels of these properties through laboratory tests or site

investigations. Future pavement design will also be efficient and economical based on the higher accuracy levels of these specific inputs.

- The results of the M-E analysis indicated the need for local calibration of the prediction models of fatigue cracking and permanent deformation. Most importantly, the future maintenance strategy in the PMS is to be taken into consideration by addressing the fatigue responses of the highway sections.

10.4 Major Contributions

This research provides a number of significant contributions. The main contribution is to incorporate improvement in assessing the overall condition of pavement. In a PMS, the predicted improvement in performance, in terms of the indices, after any treatment are set based on engineering experiences or judgement. Moreover, the remaining service life of pavement is estimated from the deterioration of the overall condition by considering only the effect of age notwithstanding the effect traffic or materials. However, this research incorporates the M-E approach in predicting the improvement in performance for specific treatment types. It also considers the effect of traffic and materials on pavement performance to precisely predict the future deterioration and subsequent remaining service life. This approach certainly overcomes the limitation of engineering judgement in assessing the overall condition of pavement which has not been done before.

Since the prediction model provides the realistic and precise prediction, it will essentially identify right time to maintenance. Moreover, the prediction model is developed based on the predicted distresses, thus, at the design stage it is possible to sketch the performance curve over the estimated life for a certain type of pavement. This will surely minimize the field evaluation work and will help in priority setting of the road sections for evaluation. Using the predicted performance curve, only road sections approaching the trigger value of maintenance will get priority for field evaluation. On the other hand, the road sections behind the trigger value of maintenance can be excluded from the priority list for annual field evaluation. This will minimize annual field evaluation works and ensure efficient utilization of the PMS budget.

Since the deterioration model is developed based on traffic and material types, the use of it will categorically ensure efficiency in the PMS, rather than using a generalized equation. The predicted required time to maintenance and estimated NPW for low to high volume traffic roads for different material types will help pavement designers and managers select treatment types efficiently, helping them make better decisions.

Since the improved performance prediction for specific treatment and corresponding deterioration due to different traffic levels are incorporated in the process of LCCA, the identified M&R strategies will be more precise and cost-effective, which will help ensure efficient allocation of maintenance budget.

The resulting accurate location reference system for pavement evaluation from the investigation of performance variability due to changes in section length, will ensure a precise method of road evaluation. This approach has never been done in any PMS before.

The incorporation of the SUR method, instead of OLS, in estimating the performance index will ensure improvement in estimating the KPI models, if unobserved factors influencing individual KPIs are correlated.

Identification of main effects and interaction effects of sensitive inputs (traffic and materials) will enable the pavement designers to put effort to attain a higher levels of accuracy for only those sensitive inputs, and thereby will ensure efficient and precise prediction of distresses.

The other significant contribution is to incorporate the M-E approach in an integrated way into pavement performance index and pavement M&R schedule. This research recommends cost-effective M&R schedules, from the LCCA by overcoming the limitation in assessing the overall condition and by incorporating the M-E approach in an integrated way into PMS, which has not been conducted in previous research. This investigation will enable pavement decision makers to decide on maintenance strategies by selecting the cost-effective maintenance option for an effective PMS.

This research develops a framework for using the M-E approach which is the state of art practice of pavement design and analysis with the PMS data to improve decision-making processes for pavement engineers.

Thus, the outcome of the empirical investigations will promote the adoption of efficient road maintenance programs for highways based on the M-E approach, having a significant impact on sustainable infrastructure asset management.

10.5 Recommendations for Future Work

The empirical investigations are carried out from the historical performance recorded in the database. However, future research can be carried out in following areas:

- In this research, the performance data used for empirical investigations are from the year 1980 and onwards. Most of the field evaluation are from the manual survey, which are subjective results of multiple raters' rating. Since the automated survey is being adopted in agency's PMS, automated performance data can be used to compare and validate the prediction models developed in this research.
- In this research, pavement deterioration models are developed based on the traffic levels and materials types. Laboratory performance tests can be conducted to validate the predicted service life for materials types and different traffic levels.

- The analysis results of bottom-up fatigue cracking justify the need for local calibration of the prediction models of fatigue cracking. Although a cluster analysis based on materials types is used in this study, for these categories a local calibration of the coefficients in the transfer models can also be investigated in future research.
- This research is carried out only for overlay activities by using specific materials. However, other M&R activities can also be investigated by using the similar framework in future research.
- This research developed models to predict the deterioration and service life of pavement. Since the investigations are done by using historical performance and predicted distresses, future field performance of these road sections can be used to compare and validate the predicted performance.

References

AASHTO (2008). Mechanistic-Empirical Pavement Design Guide: A Manual of Practice. Washington DC: AASHTO

AASHTO (2010). Guide for the Local Calibration of the Mechanical-Empirical Pavement Design Guide. Joint Technical Committee on Pavements

AASHTO (2014). Astaire Pavement M-E v. 2.0 Help Manual. AASHTOWare 2014

AASHTO, (1993). Guide of Pavement Structures. American Association of State Highway and Transportation Officials, Washington, D.C.

Ali, H.A., Tayabji, S.D. (1998). Evaluation of Mechanistic –Empirical Performance Models for Flexible Pavements. Transportation Research Board, Transportation Research Record-1629-19:169-180

Amador -Jime´nez, E., and D. Mrawira, (2011). Capturing variability in pavement performance models from sufficient time-series predictors: a case study of the New Brunswick road network. Canadian Journal of Civil Engineering, 38, 210-220.

Anastasopoulos, P.C., and F.L. Mannering (2015). Analysis of Pavement Overlay and Replacement Performance Using Random Parameters Hazard-Based Duration Models. Journal of Infrastructure Systems,Vol.21, No. 1

Ang, A.H-S, and W. H. Tang (1975). Probability Concepts in Engineering Planning and Design, Vol 1 & 2 John Wiley and Sons, New York.

ARA (2006). Pavement Structural Design Guidelines: City of Toronto. Final Report, Applied Research Associates.

Archilla, A. and S. Madanat (2001). Estimation of Rutting Models by Combining Data from Different Sources. Journal of Transportation Engineering, Vol. 127, No. 5, 2001, pp 379-389.

ASCE, (2013). American Society of Civil Engineering (ASCE) Report Card 2013, American Society of Civil Engineering.

Avakoli, A., M. Lapin, and J. Figueroa (1992). PMSC: Pavement Management System for Small Communities. Journal of Transportation Engineering, Vol. 118, No. 2, 1992, pp. 270–280.

Bandara, N. and M. Gunaratne (2011). Current and Future Pavement Maintenance Prioritization Based on Rapid Visual Condition Evaluation. Journal of

Transportation Engineering, American Society of Civil Engineers, Vol. 127, No. 2, 2011, pp. 116–123.

Beasley, T.M. (2008). Seemingly Unrelated Regression (SUR) Models as a Solution to Path Analytic Models with Correlated Errors. Journal of Multiple Linear Regression Viewpoints, 34(1), 2008.

Benjamin, J.R. and C.A. Cornel (1970). Probability Statistics and Decisions for Civil Engineers, McGraw-Hill, New York.

Bennett, C.R., A. Chamorro, C. Chen, H. de Solminihac and G.W .Flintsch (2007). Data Collection Technologies for Road Management. East Asia Transport Unit. The World Bank, Washington DC, 2007.

Cadavez, V.A.P. and A. Henningsen. (2012). The Use of Seemingly Unrelated Regression (SUR) to Predict the Carcass Composition of Lambs. working Paper, Institute of Food and Resource Economics, University of Copenhagen, 2012

Chatti, K. (2009). Effect of Michigan Multi-Axle Trucks on Pavement Distress. Executive Summary, Project RC-1504, Pavement Research Center of Excellence, Michigan State University

Chong, G.J., W.A., Phang, G.A. Wrong (1989). Manual for Condition Rating of Flexible Pavements. Distress Manifestations, Ministry of Transportation Ontario, Research and Development Branch, SP-024.

Chu, C., and P. Durango-Cohen. (2008). Empirical Comparison of Statistical Pavement Performance Models. Journal of Infrastructure System, Special Issue: Advances in Infrastructure Condition Assessment, Deterioration Modeling, and Optimal Rehabilitation, Vol. 14, No. 2, 2008, pp 138–149.

Darter, M., L. Khazanovich, T. Yu, J. Mallela (2005). Reliability Analysis of Cracking and Faulting Prediction in the New Mechanistic–Empirical Pavement Design Procedure. Transportation Research Record: Journal/Al of the Transportation Research Board, No. 1936:150–160.

de la Graza, J.M., Bish, D. R., Krueger (2010). Developing of Network Level Linear Programming Optimization for Pavement Maintenance Programming. International Conference on Computing in Civil and Building Engineering, Nottingham.

Dornan, D.L. (2002). Asset Management remedy for addressing the fiscal challenges facing highway infrastructure. International Journal of Transport Management, Vol 1, pp. 45-54

Dzotepe, G. A., K. Ksaibati (2011). The Effect of Environmental Factors on the Implementation of the Mechanistic Empirical Pavement Design Guide. Report, University of Wyoming.

El-Badawy, S. Bayomy, F. and Awed, A. (2012). Performance of MEPDG Dynamic Modulus Predictive Models for Asphalt Concrete Mixtures: Local Calibration for Idaho. Journal of Materials in Civil Engineering, No 24 (11), pp. 1412-1421.

Flintsch, G. and K.K. McGhee,. (2009). Quality Management of Pavement Condition Data Collection- A Synthesis of Highway Practice. NCHRP Synthesis 401, Transportation Research Board (TRB)

Graves, R. C., and K. C. Mahboub. (2011). Pilot Study in Sampling-Based Sensitivity Analysis of NCHRP Design Guide for Flexible Pavements. Transportation Research Record: Journal of the Transportation Research Board, No. 1947,123–135

Greene, H.W. (2003). Econometric Analysis. 5th Edition, New York University.

Guclu, A., H. Ceylan, K. Gopalakrishnan, K. and S. Kim. (2009). Sensitivity Analysis of Rigid Pavement Systems Using the Mechanistic-Empirical Design Guide Software. Journal of Transportation Engineering, 135 (8), 555-562.

Hajek, J. J., R.J. Billing, and D.J. Swan. (2011). Forecasting Traffic Loads for Mechanistic–Empirical Pavement Design. Transportation Research Record: Journal of the Transportation Research Board, 2256, 151–158.

Hall, K. D. and S. Beam (2005). Estimating the Sensitivity of Design Input Variables for Rigid Pavement Analysis with a Mechanistic–Empirical Design Guide. Transportation Research Record: Journal of the Transportation Research Board, 1919, 65–73

Hall, K. D., D. X. Xiao, and K. C.P., Wang. (2010). Calibration of the MEPDG for Flexible Pavement Design in Arkansas. Transportation Research Board (TRB) Annual Meeting CDROM.

Hass, R., W.R. Hudson and J. Zaniewski (1994). Modern pavement Management, Krieger Press, Malabar, 1994.

Henning, T., G. Jannat, C. Zhang and S. Tighe (2015). Engineering Criteria and Standards for Key Pavement Performance. Final Report, the Ministry of Transportation Ontario, 2015.

Henning, T., S.B. Costello, and M. Tapper (2013). Performance Indicator Analysis and Applying Levels of Service. New Zealand Transport Agency Research Report 529, 2013.

Hoegh, K., L. Khazanovich and M. Jensen (2008). Local Calibration of MEPDG Rutting Model for MnRoad Test Sections. Transportation Research Board (TRB), Annual Meeting CD-ROM.

HPMA (2012). M&R Optimization Analysis Manual. Highway Pavement Management Application (HPMA).

Hsiang, W., K., Lee, Y.H., Wu, P.H., (2007). Development of Fatigue Cracking Performance Prediction Models for Flexible Pavements Using LTPP Data base. Transportation Research Board (TRB) 2007 Annual Meeting CDROM.

Jackson, N. C., and J.P. Mahoney. (2007). Pavement Design and Construction Mechanistic-Empirical. Report, July 2007.

Jannat, G. T. Henning, C. Zhang, and S. Tighe (2016). Road Section Length Variability on Pavement Management Decision-Making for Ontario Highway Systems. Transportation Research Record: Journal of the Transportation Research Board, No. 2589, 2016.

Jannat, G. and S. Tighe (2015). An Experimental Design based Evaluation of Sensitivities of Mechanistic-Empirical Pavement Design Guide (MEPDG): Investigating Main and Interaction Effects of Input Factors. International Journal of Pavement Engineering, Vol. 17, No. 7, pp.615-625.

Jannat, G., F.P T Henning, S. Tighe, and L. Ninguyan (2016). Developing Engineering Criteria and Standards for Key Performance Indicators (KPIs) used in Pavement Management. Eighth International Conference on Maintenance and Rehabilitation of Pavement, Singapore, 2016.

Jannat, G. and S. Tighe (2017). Developing Performance Prediction Models based on Traffic and Materials by Incorporating Mechanistic-Empirical Approach for Ontario Highways. Transportation Research Board (TRB) Meeting, 2017

Jannat, G. and S. Tighe (2017). Investigation of Pavement Performance Index through Application of a Seemingly Unrelated Regression (SUR) Model: A Case Study on Ontario Highways. Transportation Research Board (TRB) Meeting, 2017

Jannat, G., S. Varamini, and S. Tighe (2017). Investigating Performance of Superpave through Mechanistic-Empirical Approach, Field Evaluated Performance, and Laboratory Test Results: A Case Study on Ontario Highways. Proceedings of 2017 Transportation Association of Canada (TAC) Conference.

Jannat, G., and S. Tighe (2017). Application of Probabilistic Approach for Developing of Pavement Deterioration Models based on Traffic and Materials. Proceedings of 2017 Transportation Association of Canada (TAC) Conference.

Jannat, G., and S. Tighe (2014). An Experimental Design based Evaluation of Sensitivities of Mechanistic- Empirical Pavement Design Guide (MEPDG) Predictions for Ontario's Local Calibration. 2014 Transportation Association of Canada Conference, Montreal

Jannat, G., and S. Tighe (2015). Performance based Evaluation of overall Pavement Condition Indices for Ontario Highway Systems. 2015 Transportation Association of Canada (TAC) Conference, Charlottetown, PEI

Jannat, G., and S. Tighe (2016). Developing New Performance Index for Assessing Overall Pavement Condition by Incorporating of Mechanistic-Empirical Approach for Ontario Highways. 2016 Transportation Association of Canada (TAC) Conference, Toronto

Jannat, G., and S. Tighe (2016). Investigating Life Cycle Cost Analysis to Identify Sustainable Pavement Maintenance and Rehabilitation Strategy: A Case study on Ontario Highways. 2016 Transportation Association of Canada (TAC) Conference, Toronto.

Kang, M. Adams, T. M., (2007). Local Calibration for Fatigue Cracking Models Used in the Mechanistic-Empirical Pavement Design Guide. Mid-Continent Transportation Research Symposium, Ames, Iowa, August 2007

Kazmierowski, T., Z. He, and B. Kerr (2001). A Second generation PMS for the Ministry of Transportation of Ontario. 5th International Conference on Managing Pavements, 2001.

Kubáček, L (2013). Seemingly Unrelated Regression Models. Journal of Applications of Mathematics, Vol.58 (1), 2013, pp111-123.

Labi, S. and K. Sinha. (2005). Life-Cycle Evaluation of Flexible Pavement Preventive Maintenance. Journal of Transportation Engineering, Vol 131(10), pp 744–751.

Lea, J. D., J.T. Harvey, and E. Tseng (2014). Aggregating and Modeling Automated Pavement Condition Survey Data of Flexible Pavements for Use in Pavement Management. Transportation Research Record: Journal of the Transportation Research Board, No. 2455, pp. 89-97.

Madanat, S. M., J.A. Prozzi, and M. Han (2002). Effect of Performance Model Accuracy on Optimal Pavement Design. Computer-Aided Civil and Infrastructure Engineering, Vol. 10, No. 1, pp. 22-30.

Mandapaka, V., Basheer, I., Sahasi, K., Ullidtz, P., Harvey, T. J., and Sivaneswaran, N., (2012). Mechanistic-Empirical and Life-Cycle Cost Analysis for Optimizing Flexible Pavement Maintenance and Rehabilitation. Journal of Transportation Engineering, No 138, pp 625-633

Mathew, T. V., Rao, K. V. K. (2007). IRC method of Design of Flexible Pavements. Introduction to Transportation Engineering, NPTEL May 3, 2007

Molenaar, K. R. and D. Navarro, D (2011). Key Performance Indicators in Highway Design and Construction. Transportation Research Record: Journal of the Transportation Research Board, No. 2228, pp. 51-58.

Montgomery, D.C. (2009). Design and Analysis of Experiments. 8th edition. Wiley, 2009.

Moon, R. H., and B. Perron (2006). Seemingly Unrelated Regressions. working Paper, Department of Economics University of Southern California, Département de sciences économiques, CIREQ, and CIRANO Université de Montréal, 2006.

Moulthrop, J. S., and H.L. Quintus. (2007). Mechanistic-Empirical Pavement Design Guide Flexible Pavement Performance Prediction Models for Montana. Montana Department of Transportation, Project Summary Report 8158.

Moya, J. P.A, and J. Prozzi. (2011). Development of Reliable Pavement Models, Report SWUTC/11/161025-1 Texas.

MTO (1990). Pavement Design and Rehabilitation Manual, Ministry of Transportation Ontario (MTO), 1990.

MTO (2007). Ontario Provincial Standard Specification (OPSS-1151). Material Specification for Superpave and Stone Mastic Asphalt Mixture. Ministry of Transportation, Ontario, 2007.

MTO (2007). The Formulations to Calculate Pavement Condition Indices. Ministry of Transportation, Ontario, 2007.

MTO (2010). Ontario Provincial Standard Specification (OPSS-1150): Material Specification for Hot Mix Asphalt. Ministry of Transportation, Ontario, 2010.

MTO (2012). Ontario's Default Parameters for AASHTOWare Pavement ME Design Interim Report. Material Engineering Research Office (Pavements & Foundations Section) (2012). Ministry of Transportation Ontario.

MTO (2012) Material Specification for Performance Graded Asphalt Cement- OPSS 1151. Ministry of Transportation, Ontario, 2012.

Myers, L. A., Roque, R., Birgisson, B., (2001). Propagation Mechanisms for Surface-Initiated Longitudinal Wheel-path Cracks, Transportation Research Record: Journal of the Transportation Research Board, No. 1778(1), pp 113-122

NCHRP (2004). Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures. Final Document, Appendix II-1, Calibration of Fatigue Cracking Models for Flexible Pavement, National Cooperative Highway Research Program Transportation Research Board National Research Council, 1-37A Report.

NCHRP (2011). A Manual for Design of Hot-Mix Asphalt with Commentary. Washington National Cooperative Highway Research Program (NCHRP). Transportation Research Board, 2011.

NCHRP (2013). Sensitivity Evaluation of MEPDG Performance Prediction. National Cooperative Highway Research Program, Research Results Digest 372, Transportation Research Board of National Academies.

NCHRP (2004). Optimal Timing of Pavement Preventive Maintenance Treatment Applications. National Cooperative Highway Research Program Report 523, Transportation Research Board

Ningyuan, L.(2010) . Highway Maintenance and Pavement Preservation Strategies in Canada. American Society of Civil Engineers, ICCTP 2010, pp. 3948-3956.

Ningyuan, L., and T. Kazmierowski (2008). Engineering tools and standards applied in preserving Ontario’s provincial highways, 7th Conference on Managing Pavements and Other Roadway Assets, Calgary, Alberta, Canada

Ningyuan, L., and T. Kazmierowski (2004). Impact of Performance Measures on Pavement Asset Management in Canada. 6th International Conference on Managing Pavements, Brisbane, Queensland, Australia, 2004.

Ningyuan, L., S. Tighe, A. Hamdi (2013). Impact of Using Alternative Performance Indices on Road Asset Value Assessment. International Journal of Pavements Conference, 2013

Ningyuan, L., T. Kazmierowski, S. Tighe, and R. Haas (2001). Integrating Dynamic Performance Prediction Models into Pavement Management Maintenance and Rehabilitation Programs. 5th International Conference on Managing Pavements, 2001

OHMPA. (2007). The ABCs of Superpave. The Ontario Hot Mix Producers Association, December 2007.

Olivier, P., S. Emery, E. Horak, and P. Pretorius (2010). Holistic Pavement Management - Experiences with Performance based Pavement Management in Australia and

South Africa. 4th SARF/International Road Federation Regional Conference for Africa, Cape Town, 11-14 October, 2010.

Orobio, A., and J.P. Zaniewski (2011). Sampling-Based Sensitivity Analysis of the Mechanistic–Empirical Pavement Design Guide Applied to Material Inputs. Transportation Research Record: Journal of the Transportation Research Board, No. 2226, pp 85–93.

Pandey, M.D. (2014). Engineering Risk and Reliability. Lecture Notes, University of Waterloo.

Powell, J.L. (2000). Zellner’s Seemingly Unrelated Regressions Model. working Paper, Department of Economics, University of California, Berkeley, 2000.

Prozzi , J. A. and S. M. Madanat (2004). Development of Pavement Performance Models by Combining Experimental and Field Data. Journal of Infrastructure Systems, Vol. 10, No.1, pp. 9-22.

Prozzi , J. A. and S. M. Madanat (2000). Using Duration Models to Analyze Experimental Failure Data. Transportation Research Record: Journal of the Transportation Research Board, No. 1699, pp 87-94.

Prozzi, J.A. (2001). Modelling of pavement performance by Combining Field and Experimental Data. Doctor of Philosophy Thesis, University of California, Berkeley, 2001.

Prozzi, J.A. and F. Hong (2008). Transportation Infrastructure Performance Modeling through Seemingly Unrelated Regression Systems. Journal of Infrastructure Systems, ASCE, Vol.14, No. 2, pp129–137.

Prozzi, J.A. and S. M. Madanat (2003). Incremental Nonlinear Model for Predicting Pavement Serviceability. Journal of Transportation Engineering, Vol. 129, No. 6, pp. 635-641.

Retherford, J. Q., and M. McDonald. (2011). Estimation and Validation of Gaussian Process Surrogate Models for Sensitivity Analysis and Design Optimization Based on the Mechanistic–Empirical Pavement Design Guide. Transportation Research Record: Journal of the Transportation Research Board, 2226, 119–126.

Salem, H.M.A., (2008). Effect of Excess Axle Weights on Pavement Life. Emirates Journal for Engineering Research, Vol13 (1), pp 21-28

Schram, S., and M. Abdelrahman. (2006). Improving Prediction Accuracy in Mechanistic-Empirical Pavement Design Guide. Transportation Research Record: Journal of the Transportation Research Board, No1947, pp 59-68

Schwartz, W.C., and R.L. Carvalho. (2007). Implementation of the NCHRP 1-37A -Design Guide: Evaluation of Mechanistic-Empirical Design Procedure. Final Report MDSHA Project No. SP0077B41 UMD FRS No. 430572, Maryland State Highway Administration Volume: 2

Siraj, N., Y.A Mehta, K.M. Muriel, and R.W. Sauber (2009). Verification of mechanistic-empirical pavement design guide for the state of New Jersey. Department of Civil and Environmental Engineering, Rowan University, Glassboro, NJ, USA; Taylor & Francis Group.

TAC (2013). Pavement Asset Design and Management Guide. Transportation Association of Canada (TAC).Prepared by the University of Waterloo, 2013

Takada, H., A. Ullah, and Y.M. Chen (1995). Estimation of Seemingly Unrelated Regression Model when Error Covariance Matrix is Singular. Journal of Applied Sciences, 22 (4), pp 517-530.

Tighe, S., K. Huen, and R. Hass (2007). Environmental and Traffic Deterioration with Mechanistic-Empirical Pavement Design Model. Transportation Research Record: Journal of the Transportation Research Board, Vol 1989 (2), pp 336-343

Tighe, S.L., L. Ningyuan, and T. Kazmierowski (2008). Evaluation of Semi-automated and Automated Pavement Distress Collection for Network-Level Pavement Management. Transportation Research Record: Journal of the Transportation Research Board, No. 2084, pp11–17.

Timm, D.H., R.E. Turochy, R.E., and K.P. Davis (2010). Guidance for ME Pavement Design Implementation. Final Report, ALDOT Project 930-685

TRC (2011). Sensitivity Analysis for Flexible Pavement Design with the Mechanistic Pavement Design Guide. Transportation Research Circular E-C155

Van der Lei, T., R. Schoenmaker, T. Van, and M. Klok (2014). Tool. Performance Management Practices in Europe and the USA. Transportation Research Board Annual Meeting, 2014

Velasquez, R., K. Hoegh, I. Yut, N. Funk and G. Cochran, M. Marasteanu, L. Khazanovich (2009). Implementation of the MEPDG for New and Rehabilitated Pavement Structures for Design of Concrete and Asphalt Pavements in Minnesota. Final Report, Minnesota Department of Transportation, Research Services Section.

Walaa, S. M, , J.A. Daniel, F. Zhoud and T. Bennerte (2011). Evaluation of the effects of hot mix asphalt density on mixture fatigue performance, rutting performance and MEPDG distress predictions. International Journal of Pavement Engineering, Vol 2 (21), pp-161-175

Walid, M. N., (2001). Utilization of Instrument Response of SuperPaveTM Mixes at the Virginia Smart Road to Calibrate Laboratory Developed Fatigue Equations. Virginia Polytechnic Institute and State University, Blacksburg, VA 24061 Blacksburg, Virginia, July 2001

Wardle, L.J., (1998). Layered Elastic Design of Heavy Duty and Industrial Pavements. AAPA Pavements Industry Conference, Surfers Paradise, Australia, 1998.

Whiteley, L., S. Tighe, and Z. Zhang (2005). Incorporating Variability into Pavement Performance Models and Life Cycle Cost Analysis for Performance-Based Specification Pay Factors. Transportation Research Record: Journal of the Transportation Research Board, No. 1940, pp 13-20

WSDOT (2005). Washington State Department of Transportation's Pavement Guide Interactive. Washington State Department of Transportation.

Yang, H. H., (1993). Pavement Analysis and Design. Prentice Hall, Englewood Cliffs, New Jersey 1993

Yu, B., and Q.J. Lu (2013). An Improved Pavement Maintenance Optimization Methodology: Integrating LCA and LCCA. Transportation Research Part A, No. 55 (2013), pp 1–11

Yu, J., E. Chou, and Luo, Z (2003). Development of Linear Mixed Effects Models for Predicting Individual Pavement Conditions. Journal of Transportation Engineering, American Society of Civil Engineers, Vol. 133, No. 6, 2003, pp. 347-354.

Zellner, A (2006). Seemingly Unrelated Regressions. International Encyclopedia of Social Sciences, University of Chicago, 2006.

Zellner, A. (1962). An Efficient method of estimating seemingly unrelated regression equations and test for aggregation bias. Journal of American Statistical Association, No. 57, pp.348–368.