Copyright

by

Oscar Daniel Galvis Arce

2017

The Thesis Committee for Oscar Daniel Galvis Arce
Certifies that this is the approved version of the following thesis:

FRAMEWORK TO ESTIMATE THE BENEFIT-COST RATIO OF PAVEMENT SKID IMPROVEMENTS AT THE NETWORK LEVEL

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor: ______________________________
Zhanmin Zhang

____
Michael R. Murphy

FRAMEWORK TO ESTIMATE THE BENEFIT-COST RATIO OF PAVEMENT SKID IMPROVEMENTS AT THE NETWORK LEVEL

by

Oscar Daniel Galvis Arce, B.Sc.

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE IN ENGINEERING

The University of Texas at Austin

May 2017

Dedication

To God, my parents, and my wife.

Acknowledgements

I would like to thank Dr. Zhanmin Zhang for all his support during these academic years. His guidance and counsel helped me to reach this goal in my life. Furthermore, his suggestions on this thesis were valuable for my professional growth.

I would also like to thank Dr. Michael Murphy for his support. His feedback on this document has been beneficial for my learning process. Likewise, my experience working with him advanced my professional development. My sincere appreciation goes to Dr. Hui Wu for her insights in my research, and her help obtaining the data for the case study. Similarly, I thank Caitlan Zilligen for her valuable comments while writing the document.

I would like to thank my parents Edgar Galvis and Patricia Arce for their support and motivation to pursue this degree. I would like to thank my wife, Marcela Guilombo, which is always there for me. Finally, I would like to thank God who made all things possible for me.

Abstract

FRAMEWORK TO ESTIMATE THE BENEFIT-COST RATIO OF PAVEMENT SKID IMPROVEMENTS AT THE NETWORK LEVEL

Oscar Daniel Galvis Arce, MSE

The University of Texas at Austin, 2017

Supervisor: Zhanmin Zhang

Research has proven that low values of pavement skid increase crash risk. Minimum skid thresholds have been established in order to screen projects for further testing and improvements. Skid resistance values are used in addition to crash data, pavement condition data, and roadway features to select and prioritize skid improvement projects. Furthermore, skid resistance performance models have been developed in order to capture the skid deterioration over time. However, the aforementioned studies did not quantify the economic impact of skid improvements over a time period for a network.

This thesis fills this information gap, by providing a framework that quantifies the Benefit-Cost Ratio (BCR) of skid resistance improvements at the network level. A skid deterioration model is developed using the Markov Chain process, in order to account for the base case scenario when no treatment is applied. Benefits are quantified as the reduction of expected crashes compared to the base case scenario, using the concept of Crash Rate Ratio (CRR). Costs are quantified as the costs of pavement resurface treatments that improve skid. A sample of highway sections that comprise 564 lane-miles

in Texas is evaluated to demonstrate the applicability of the proposed methodology. As a result, a Benefit-Cost Ratio curve was generated for different minimum skid thresholds.

Table of Contents

List of Tables xii

List of Figures xiii

Chapter 1: Introduction 1

- 1.1 Introduction to the Problem 1
- 1.2 Research Motivation 2
- 1.3 Research Objectives 2
- 1.4 Research Scope 2
- 1.5 Research Outline 3

Chapter 2: Literature Review 4

- 2.1 Relation Between Crashes and Skid Resistance 4
- 2.2 Method to Measure Skid Number 6
- 2.3 Quantification of Impact of Skid Resistance and Crash Risk at the Network Level 9
- 2.4 Definition of Minimum Skid Thresholds 13
- 2.5 Skid Deterioration Models 15
- 2.6 Previous Benefit-Cost Ratio Analyses of Skid Improvements 17
- 2.7 Summary of Literature Review 18

Chapter 3: Proposed Framework 20

Chapter 4: Markov Chain Principles 23

- 4.1 Types of Markov Chains 23
- 4.2 Advantages and Disadvantages of Finite-Space, Time-Discrete, and Time-Homogenous Markov Chain Models 25
- 4.3 Definition of a Finite-Space, Time-Discrete and Time-Homogenous Markov Chain 27
- 4.4 Estimation of Transition Probability Matrix 32
- 4.5 Estimation of the Future Condition of the System 32

4.6 Optimization of the Transition Probability Matrix 33
4.7 Develop the Transition Probability Matrix For Heterogeneous Groups.34
4.8 Summary 35
Chapter 5: Model Skid Resistance Deterioration..37
5.1 Select Skid Resistance Performance Measure 38
5.2 Define Skid Condition States...39
5.3 Estimate Deterioration Transition Probability Matrix 40
5.3.1 Select the Data to Model the Deterioration................................40
5.3.2 Select the Training and Test Sets...42
5.3.3 Develop Transition Probability Matrix and Predict the Future Condition..44
5.3.4 Optimize the Transition Probability Matrix...............................45
5.4 Perform a Statistical Test of the Prediction 49
5.5 Summary 52
Chapter 6: Estimate Costs for Maintaining Skid Resistance 54
6.1 Define Skid Resistance Maintenance Thresholds..................................55
6.2 Define a Maintenance Transition Probability Matrix for Each Threshold57
6.3 Select Unit Cost of Skid Resistance Treatments....................................59
6.4 Estimate Policy Cost 62
6.4.1 Estimation of Network Treatment Cost for a Specific Goal.......62
6.4.2 Estimation of Network Treatment Cost for Multiple Maintenance Goals 65
Chapter 7: Estimate Crash Reduction Benefits..66
7.1 Assess Current Safety Condition in the Network 67
7.2 Link Expected Crashes with Skid Resistance Through CRR 68
7.3 Estimate Expected Crashes With and Without Maintenance 71
7.4 Estimate Monetary Benefit from Crash Reduction................................72
Chapter 8: Benefit-Cost Ratio Analysis...75
8.1 Estimation of Benefit-Cost Ratio for Multiple Maintenance Goals 75
8.2 Development of One-Variable Scenarios 77

Chapter 9: Case Study 79
9.1 Description of Initial Skid Database 79
9.2 Model Skid Resistance Deterioration 79
9.2.1 Define the Skid Resistance Performance Measure 79
9.2.2 Define Skid Condition States..80
9.2.3 Estimate Deterioration Probability Matrix..................................81
9.2.3.1 Select the Data to Model the Deterioration.....................81
9.2.3.2 Select the Training and Test Sets....................................82
9.3.2.3 Develop the Transition Probability Matrix and Prediction of the Future Condition 83
9.3.2.4 Optimize the Transition Probability Matrix....................84
9.2.4 Perform a Statistical Test of the Prediction 86
9.3 Estimate Costs for Maintaining Skid Resistance....................................88
9.3.1 Define Skid Resistance Maintenance Threshold 88
9.3.2 Define a Maintenance Transition Probability Matrix for Each Threshold 88
9.3.3 Select Unit Cost of Skid Resistance Treatments.........................91
9.3.4 Estimate Policy Costs 91
9.4 Estimate Crash Reduction Benefits 92
9.4.1 Assess Current Road Safety Condition.......................................92
9.4.2 Link Expected Crashes with Skid Resistance Through CRR 93
9.4.3 Estimate Expected Crashes With and Without Maintenance 96
9.4.4 Estimate Monetary Benefit from Crash Reduction.....................96
9.5 Benefit-Cost Ratio Analysis 98
9.6 Policy Recommendations..100
Chapter 10: Summary of Findings and Topics for Future Research 102
10.1 Summary of Research Findings 102
10.2 Limitations 104
10.3 Topics for Future Research 105

Appendix A - Results of the BCR Analysis..107

Bibliography 110

Vita 115

List of Tables

Table 1: Summary of Skid Thresholds Established by California, Florida, Michigan and Virginia 14
Table 2: Condition States Used to Model Skid Resistance..... 81
Table 3: Number of Sections Observed (and Predicted) in Each Condition State 2012-2015 for the Training Set with Non-Optimized TPM..... 83
Table 4: Relative Error of Prediction for the Training Set with Non-Optimized TPM.... 84
Table 5: Transition Probability Matrix Optimized for the Training Set..... 84
Table 6: Number of Sections Observed (and Predicted) in Each Condition State 2012-2015 for the Training Set with the Optimized TPM..... 85
Table 7: Relative Error of Prediction for the Training Set with Optimized TPM..... 85
Table 8: Results of the Chi-Square Test for the Training Set..... 86
Table 9: Number of Sections Observed (and Predicted) in Each State 2012-2015 for the Test Set with the Optimized TPM 87
Table 10: Relative Error of Prediction for the Test Set with Optimized TPM..... 87
Table 11: Results of the Chi-Square Test for the Test Set..... 87
Table 12: Safety Parameters Used to Estimate the Expected Number of Crashes in the Network in the Base Year (2015) 93
Table 13: CRR-SN Associated For Each Condition State..... 94
Table 14: Network Condition in 2015 95
Table 15: Percentage of Crashes and Crash Rate per Lane-Mile Per Year for Each Condition State..... 95
Table 16: Summary of Crash Data for the Austin District in 2015 97
Table 17: Marginal Benefit-Cost Ratio for Each Condition State with Average Maintenance Costs..... 99
Table 18. Results of the BCR analysis..... 107

List of Figures

Figure 1: Distribution of Total Crashes as a Function of SN (2008-2011) 11
Figure 2: Distribution of Lane Miles in the Network as a Function of SN (2008-2011) . 12
Figure 3: CRR-SN Curve for Statewide Crashes.. 13
Figure 4: Framework for Developing the Benefit-Cost Ratio of Skid Improvements 21
Figure 5: Example of a Markov Rate Diagram and Transition Probability Matrix for a Four-State a) Regular Markov Chain, b) Progressive Markov Chain, and c) Sequential Markov Chain. 31
Figure 6: Framework for Developing the Skid Resistance Deterioration Model 37
Figure 7: Example of the Holdout Cross-validation 43
Figure 8: Example of the K-Fold Cross-validation for *k*=3 43
Figure 9: Example of the Random Sampling Cross-validation for *k* Subsampling 44
Figure 10: Framework for Estimating the Skid Resistance Maintenance Costs 54
Figure 11: Framework for Estimating Crash Reduction Benefits 66
Figure 12: Framework for the Benefit-Cost Ratio Analysis 75
Figure 13: Cumulative Frequency of the Number of Sections for Each Skid Number for State Condition 1 89
Figure 14: Cumulative Frequency of the Number of Sections for Each Skid Number for State Condition 6 90
Figure 15: Maintenance Costs for Different Maintenance Goals in the Network 92
Figure 16: Estimated Crash Reduction in the Network for Years 2015-2018 for Different Maintenance Goals 96
Figure 17: Benefit-Cost Ratio for Different Maintenance Goals 98
Figure 18: Marginal Benefit-Cost Ratio for Each Condition State with Average Maintenance Costs 100

Chapter 1: Introduction

1.1 Introduction to the Problem

Research has proven that low values of pavement skid increase crash risk. Since 1970s, different researchers have analyzed the effect of low pavement skid in crashes (specially wet crashes) in Europe and the United States. Multiple DOTs have established minimum skid thresholds as guidelines, in order to screen projects for further testing and improvements. Skid resistance values are used in addition to crash data, pavement condition data, and roadway features to select and prioritize skid improvement projects.

Likewise, skid resistance performance models have been developed in order to capture the skid deterioration over time. These models analyze the long-term performance of skid and, some of them, account for the stochastic nature of the deterioration process. However, the aforementioned studies have not been used to quantify the economic impact of skid improvements over a time period for a network.

This thesis fills this information gap by providing a framework that quantifies the Benefit-Cost Ratio (BCR) of skid resistance improvements at the network level. In order to predict the condition of the network if no treatment is applied, a skid deterioration model is developed using a finite-state time-discrete time-homogenous Markov Chain process. Benefits are quantified as the reduction of expected crashes compared to the base case scenario using the concept of Crash Rate Ratio (CRR). Costs are quantified as the cost of pavement resurface treatments that improves skid. A sample of highway sections that comprise 564 lane-miles in Texas is evaluated to demonstrate the applicability of the proposed methodology. As a result, a Benefit-Cost Ratio curve was generated for different minimum skid thresholds.

1.2 RESEARCH MOTIVATION

There is a significant interest in evaluating and understanding roadway conditions, including pavement skid resistance at crash locations, to help develop strategies to reduce crashes. Multiple studies have recommended thresholds for minimum skid resistance, but few have quantified the relationship between crashes and skid values. Likewise, there is a need to link skid deterioration models, skid conditions, and crashes in order to estimate the potential economic benefits of skid improvements for a network.

1.3 RESEARCH OBJECTIVES

The purpose of this thesis is to provide a framework to estimate, at the network level, the expected Benefit-Cost Ratio of skid improvement. In order to achieve this, four major objectives have been defined:

1. Develop a reliable skid resistance deterioration model over time for pavements with asphalt concrete or other asphaltic resurfacing treatments such as seal coats or micro-surfacing;
2. Incorporate, in the deterioration model, the maintenance impact of different asphaltic pavement resurfacing treatments and their costs at the network-level;
3. Estimate the expected reduction in the number of crashes due to skid improvements (maintenance) at the network level; and
4. Estimate the Benefit-Cost Ratio of these skid improvements.

1.4 RESEARCH SCOPE

The proposed framework focuses on the roadway network analysis; thus, the results should not be used to analyze the benefits of skid improvements at the project-level. Likewise, the framework does not include project selection, treatment selection, or scheduling optimization. The proposed framework is developed for flexible pavements only. Moreover, the skid value is considered as the only criteria to decide whether or not to apply a pavement resurface treatment, while in the real decision processes, a combination of factors may be considered. Finally, the proposed framework is developed over a four-year horizon and the analysis perform is applied both for dry and wet weather crashes.

1.5 Research Outline

The following is the research outline of this thesis:

Chapter 2 is the literature review of previous studies related to skid deterioration models, the relationship between crashes and skid, and economic analyses done for skid improvements. Chapter 3 presents an overview of the framework proposed in this thesis. Chapter 4 describes the Markov Chain principles and how this stochastic model can be applied for infrastructure deterioration. Chapter 5 describes the development of the Markov Chain (MC) deterioration model for pavement skid deterioration. Chapter 6 describes the estimation of maintenance costs for different skid thresholds. Chapter 7 describes the estimation of the economic benefits due to expected crashes reduction. Chapter 8 describes the estimation of the Benefit-Cost Ratio and subsequent analyses of the results. Chapter 9 presents the application of the framework in a case study. The analysis is done to a portion of the Austin District network, in Texas. Finally, Chapter 10 presents the major findings and conclusions of the thesis.

Chapter 2: Literature Review

2.1 Relation Between Crashes and Skid Resistance

Globally, the United Nations, with the leadership of the World Health Organization (WHO), considers road safety as a public health challenge worldwide. WHO launched the Decade for Road Safety Action in 2010, an initiative aimed to reduce the expected number of fatalities by 50 percent in 2020 (World Health Organization, 2016). In the United States, 35,092 people died and 2.44 million people were injured as a consequence of crashes in 2015. The percentage increase of fatalities between 2014 and 2015 was 7.2 percent, which is the second largest after 1965 to 1966 (National Highway Traffic Safety Administration, 2016). In the case of Texas, the number of fatalities in crashes was 3,531 in 2015, which represents an estimated economic loss of almost $37.7 billion (Texas Department of Transportation, 2016).

Multiple factors are typically involved in traffic accidents, and pavement friction can be one of these contributing factors (Pratt, et al., 2014). The theory of the tire-pavement interaction can be explained as a supply-demand problem, defined as the Margin of Safety. The Margin of Safety is the difference between the demand of friction and the supply of friction. The factors that contribute to the demand of friction are the precipitation, traffic volume, amount of trucks, posted speed, geometrics, and frequency of vehicle stops. The factors that contribute to the supply of friction are the cross slope, pavement design life, and macro texture and micro texture of the aggregates (Texas Department of Transportation, 2006). When the margin of safety is decreased, the risk of crashes increases (Pratt, et al., 2014).

Worldwide, there have been multiple studies assessing whether there is a relationship between pavement friction and crashes. However, there are also multiple methods to measure the pavement friction, which result in research analyses that are difficult to compare to each other (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000) (Bustos, Echaveguren, Solminihac, & Caroca, 2006). In general, European countries measure the skid using the sideways force coefficient, while in the U.S., the skid is measured using the tractive force coefficient. The sideways force coefficient is measured with the Side-force Coefficient Routine Investigation Machine (SCRIM) test, while the tractive force coefficient is measured following the ASTM E274 skid test (Corsello, 1993). The present study focuses on the tractive force coefficient as this method is commonly applied in the U.S.

The ASTM E274-06 “Standard Test Method for Skid Resistance of Paved Surface using a Full-Scale Tire” estimates an indicator called skid number (SN), which is an indirect estimation of the pavement friction. Theoretically, the SN can attain a value that ranges from 1 to 100. Multiple researchers have studied the relationship between skid resistance and crashes and have pointed out that skid resistance is a significant factor in roadway crashes. Milton et al. (2008) found that increasing skid resistance resulted in a decrease in the likelihood of possible injury and an increase in the probability of property damage crashes; in other words, increasing skid causes crash severity to reduce. Moreover, Kuttesh (2004) indicated that the risk of wet accident crashes increased as the skid number decreased, based on a dataset from the Virginia Wet Accident Reduction Program. In addition, Kuttesch recommended a SN(64)*S* (that is, a skid number measured at 64 kilometers per hour (40 miles per hour) with a smooth tire) between 25 and 30 for all sites, and a SN(64)*S* of 40 for interstate highways. Similarly, Pardillo and Pina (2009) analyzed skid values from 1,750 kilometers (1,090 miles) of two-lane rural roads in Spain for a period of ten years. The researchers performed a before-after study on sections that improved the SCRIM value from below 50 to above 60, and found that skid improvement yielded significant reduction in wet-pavement crash rates averaging more than 68 percent. In recent years, the Federal Highway Administration (2014) compiled various instances where skid improvements caused crash reductions over time. These researchers suggested the importance of maintaining adequate levels of pavement friction to reduce wet weather crash risk.

2.2 Method to Measure Skid Number

The method to measure the skid number is specified by the ASTM E 274-06 "Standard Test Method for Skid Resistance of Paved Surface Using a Full-Scale Tire" (ASTM International, 2015). There are two types of tires that can be used in the test, which are specified by the ASTM E501 (for the ribbed tire) and ASTM E524 (for the smooth tire). The test uses a locked-wheel skid trailer at a constant speed of 40 mph, 45 mph, or 50 mph. It is important to consider both the type of tire and the test speed when comparing skid results from different studies based on the ASTM test method because 1) skid numbers typically decrease with increasing speed, all other factors remaining constant; and 2) smooth tires result in lower skid numbers than ribbed tires, all other factors remaining constant (ASTM International, 2015). Though there are studies that considered the variation in SN due to different test parameters such as the ribbed and smooth tire (Choubane, Holzschuher, & Gokhale, 2006), as well as different speeds (Henry & Wambold, 1992), the conversion is not easy to establish nor suggested (ASTM International, 2015). These differences can lead to different thresholds, policies, and deterioration models.

During the locked wheel trailer skid test, water is sprayed in front of the test tire to produce a water film thickness. After the application of the water film (0.5 seconds later), the test wheel brake is applied until the wheel is locked completely. The wheel remains locked during a defined interval (between 1.0 s and 3.0 s) and then is released. The ribbed tire is relatively insensitive to the water film thickness, while the smooth tire is more sensitive to water film thickness (Choubane, Holzschuher, & Gokhale, 2006). The values that are obtained during testing include the test speed, the tractive force 'F' between the tire and the pavement surface, and meta-data about the test equipment, which is recorded to evaluate and identify possible equipment issues if questions arise about test values (ASTM International, 2015). TxDOT uses a one-channel skid trailer system which requires assuming that W, the dynamic vertical load on test wheel, is equal to 1,085 +/- 15 lbs during skid testing (Zimmer & Fernando, 2013). The SN is estimated according to the following equation:

$$SN(V)T = 100 * \left(\frac{F}{W}\right) \tag{1}$$

where,

SN = Skid Number, which is a function of speed and the type of tire.

V = Speed in which the test is conducted (in miles per hour or kilometer per hour).

T = Indication of the tire used in this test (ribbed or smooth).

F = Tractive horizontal force applied to the tire (in Pounds or Newton).

W = Vertical load applied to the tire (in Pounds or Newton).

The SN can be estimated in either International System of Units (SI) or Imperial System of Units. By default, the test parameters used for the test are in Imperial units. When reporting the values, the test speed in miles per hour is reported after the "SN" (for example, SN40 represents the skid number measured at a speed of 40 miles per hour). If the test is applied using SI, the speed is within parenthesis (for example, SN(64) represents the skid number measured at a speed of 64 kilometers per hour – 40 miles per hour). Likewise, an R after the speed represents a test performed with a ribbed tire, while the smooth tire is indicated with an S (for example, SN40R vs SN40S).

TxDOT conducts skid testing using a locked-wheel skid trailer, specified by ASTM E274 (Texas Department of Transportation, 2008). The test is conducted at a speed of 50 mph with an average water film thickness of 0.5 mm (1/50 inch) and a smooth tire. TxDOT collects skid resistance data on approximately 50 percent of Texas Interstate Highway lane miles and 25 percent of the remaining Texas network lane miles annually. Skid data is primarily collected on the main lanes of roadways rather than on frontage roads (Long, Wu, Zhang, & Murphy, 2014).

The ASTM E-274 Standard indicates an estimated standard deviation of 2 SN in the skid measured when the test is repeated. Furthermore, it was established that there is no significant correlation between the standard deviation and the arithmetic mean set of skid test values; that is, the standard deviation does not increase or decrease with the mean value of SN (ASTM International, 2015). TxDOT estimated a root mean square error of less than +/- 5 SN in their measurements (Texas Department of Transportation, 2008). For the rest of the document, SN refers to SN at 50 mph and smooth tire, as it is applied in Texas, unless indicated otherwise.

TxDOT uses a one-channel locked wheel system (which measures only the dynamic horizontal forces), while in other parts of the U.S. a two-channel locked wheel system (which measures both dynamic horizontal forces and vertical loads) is used. Zimmer and Fernando (2013) analyzed the difference in skid measurements between these two systems, and discussed how the TxDOT skid collection process could be improved. The researchers found differences in the measurements, especially in non-tangent sections. The researchers recommended TxDOT to change the skid trailer fleet from one-channel to two-channel skid trailers, following the trend in other parts of the United States.

2.3 Quantification of Impact of Skid Resistance and Crash Risk at the Network Level

The impact of skid resistance on crash rates, at the network level, has been explored for the state of Texas. Pratt et al. (2014) developed a framework to assess the need for High Friction Surface Treatments (HFST) as a potential option for reducing the run-off-road (ROR) crashes on horizontal curves. This study analyzed the impact of skid using the concept of margin of safety; that is, the study quantified the difference between friction supply and friction demand. The variables included in the analysis were average daily traffic, curve radius, deflection angle, tangent speed, average lane width, average shoulder width, grade, crash history, super elevation rate, and skid number. The researchers developed an Excel-based software to estimate the margin of safety and expected crashes based on the aforementioned parameters. The study concluded that skid is a relevant factor in the run-off-road crashes for Texas on horizontal curves.

In 2014, Long et al. conducted a study to establish the maintenance thresholds for skid resistance to reduce the potential impact on highway safety due to reduced funding. This study developed a quantitative relationship between crash risk and skid resistance using the concept of Crash Rate Ratio (CRR). The advantage of the CRR method is that it allows analysts to quantify the impact of skid resistance at the network level.

The CRR is the ratio of the cumulated percentage of crashes and the cumulated percentage of total lane-miles below a given skid condition in the network. If crashes are independent of the pavement skid, this ratio would have a value varying above or below one. Conversely, if there is a relationship between crashes and skid values, the ratio, plotted for a range of skid values, would show a trend of increasing crash risk for decreasing skid values. Furthermore, the ratio provides a quantitative relationship between crashes and skid values. The CRR is estimated using Equation 2.

$$CRR = \frac{P_{CR}^{SN}}{P_{LM}^{SN}} \quad (2)$$

where:

CRR = Crash Rate Ratio.

P_{CR}^{SN} = Cumulative percentage of total crashes below a specific SN.

P_{LM}^{SN} = Cumulative percentage of total lane-miles at or below a specific SN.

Long et al. (2014) estimated the CRR curves using data from 2008 to 2011 for the entire state of Texas. Figure 1 presents the frequencies and cumulated crashes as a function of SN. Figure 2 presents the frequencies and cumulated pavement sections in the network as a function of SN. As can be seen from the two figures, the cumulative frequencies are different with higher frequencies of crashes in low skid sections: this means that lower skid sections have a higher cumulative number of crashes.

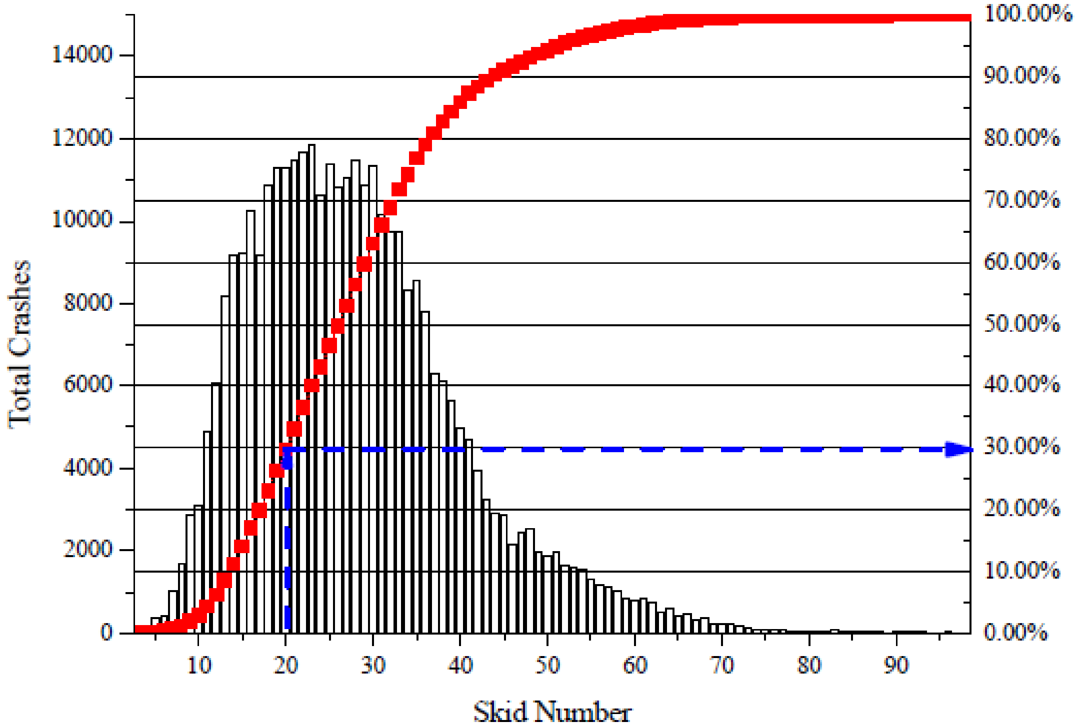


Figure 1: Distribution of Total Crashes as a Function of SN (2008-2011)

Note: Reprinted from "Quantitative Relationship between Crash Risk and Pavement Skid Resistance", by K. Long et al, 2014. Report FHWA/TX-13/06713-1. Copyright by the Center for Transportation Research.

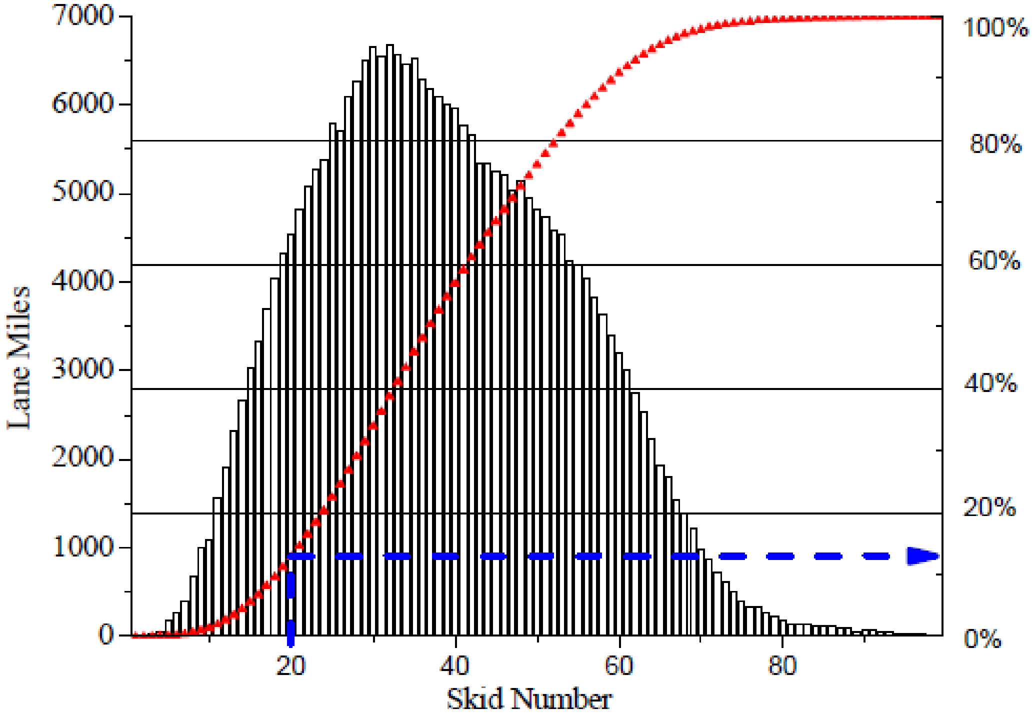


Figure 2: Distribution of Lane Miles in the Network as a Function of SN (2008-2011)

Note: Reprinted from "Quantitative Relationship between Crash Risk and Pavement Skid Resistance", by K. Long et al, 2014. Report FHWA/TX-13/06713-1. Copyright by the Center for Transportation Research.

As a result of the CRR analysis, it was found that the crash rate risk increases significantly when SN declines below SN 28. In addition, Long et al. (2014) quantified the relationship between the CRR and the skid resistance in terms of the SN. Figure 3 presents the estimation of the CRR-SN curves, showing the general trend of increase of crash risk for low values of skid. As a result, the skid condition of the network can be linked to the expected number of crashes using this relationship.

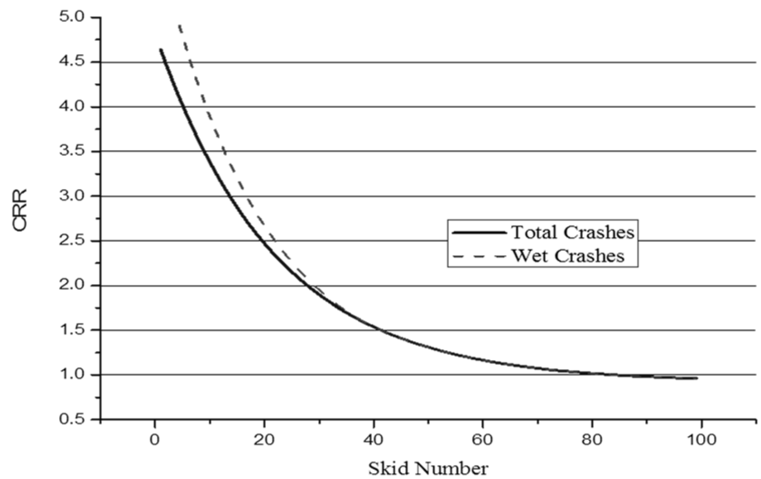


Figure 3: CRR-SN Curve for Statewide Crashes

Note: Reprinted from "Quantitative Relationship between Crash Risk and Pavement Skid Resistance", by K. Long et al, 2014. Report FHWA/TX-13/06713-1. Copyright by the Center for Transportation Research.

The function between CRR and the SN can be expressed as:

$$CRR = a * e^{-b * SN_{50s}} + c \quad (3)$$

where:

a, b, c = Regression coefficients

e = Base of the natural logarithm

SN_{50s} = Skid Number tested with smooth tire at 50 mph

2.4 Definition of Minimum Skid Thresholds

In recent years, there has been a renewed interest in pavement resurface treatments: as part of the Wet Weather Crash Reduction Program, national and state agencies are analyzing improving skid as a potential strategy to reduce crashes (Federal Highway Administration, 2014). The maintenance thresholds at the network level are established by each state independently, as well as the test parameters (such as test speed and units). To give an idea of these differences, Table 1 summarizes the skid thresholds established in four states in the U.S. (Federal Highway Administration, 2014b).

Table 1: Summary of Skid Thresholds Established by California, Florida, Michigan and Virginia

State	Skid Threshold
California	30 (SN40R)
Florida	Posted speed >45 mph = 30 (FN40R); Posted speed < 45 mph = 28 (FN40R)
Michigan	30 (SN40R)
Virginia	20 (SN40S)

Note: FN stands for Friction Number, and it is equivalent to "Skid Number", but it is used in Florida as FN for legal reasons (Jackson, 2008).

In the case of Texas, McCullough and Hankins (1966) analyzed 517 rural sections to estimate the relationship between crashes and low skid values. The researchers recommended a minimum friction coefficient of 0.31 at a speed of 20 miles per hour, and 0.24 at a speed of 50 miles per hour as the thresholds for Texas highways. Long et al. (2014), based on the quantification of the CRR-SN curves at the network level, proposed three thresholds based on these curves: Minimum SN (SN = 14), Vigilant SN (SN = 28) and Desirable SN (SN = 73). Below the Minimum SN, the crash rate increases significantly. Between the Vigilant and Minimum SN, conducting project-level testing is recommended. Between Desirable and Vigilant SN, continued network-level vigilance regarding the skid scores is recommended. Finally, the Desirable SN (and above) are considered to be the SN values where skid improvements will yield little reduction in crash rates (see Figure 3).

2.5 Skid Deterioration Models

The deterioration of skid resistance is important in order to estimate the condition of the network when no pavement resurfacing treatment is applied. This is known as the base scenario. The different models that describe the long-term behavior of skid can be summarized into two categories: 1) models in which skid deteriorates for some years until it reaches a final, constant value; and 2) models in which the skid deterioration continues without reaching a final, constant value.

In the first category, the deterioration models are based on the assumption that skid resistance drops from an initial value (at the beginning of the pavement life) to a final, constant value that is steady over time. The first model was proposed in the 1970s and later was refined by Diringer and Barros (1990). The researchers explained that pavement aggregates have a polishing state where the skid drops until it reaches an equilibrium state. Different modifications to this model have been proposed since then, with different formulations for the skid drop, but the principle of a constant final value is kept (McDonald, Crowley, & Turochy, 2006). At the beginning of the pavement life, the skid resistance decays exponentially, until it reaches a final value. Likewise, skid can experience an oscillation around the final value due to seasonal variation. Usually the final value is associated with the characteristics of the pavement aggregates, asphalt mix, and traffic (Echaveguren, de Solminihac, & Chamorro, 2010). For this reason, existing prediction models following this approach use project-level data, such as the aggregate characteristics, to estimate the final condition of skid (Awoke, 2011).

Skid deterioration models in the second category include deterministic and stochastic methods. Deterministic models provide an approach for predicting the condition of skid based on multiple linear regressions of historical values and other parameters (such as traffic and aggregate characteristics). In contrast, stochastic models for skid have used the Markov Chain and Artificial Intelligence (Echaveguren, de Solminihac, & Chamorro, 2010). Stochastic models have the advantage of greater predictive power because the deterioration process is stochastic (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015).

Fulop et al. (2000) developed a Markov Chain model in order to predict the future friction condition of the network for Hungarian asphalt pavement highways. Based on network-level data from 1994 to 1997, a sample of the network without any treatment was used to estimate the deterioration from one year to another. The model successfully captured the deterioration of the pavement friction for a 4-year time period.

The Markov Chain processes have advantages when modeling infrastructure deterioration. First, Markov Chains models have been used in modeling the deterioration of pavements and bridges (Kallen, 2007) (Yang, 2004) (Panthi, 2009) (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). Second, Markov Chain models are stochastic, and capture the stochastic nature of deterioration of pavements. Third, Markov Chains have the advantage of requiring less data than other models because the model can be applied with small time series, and it is not difficult to incorporate new data if required. However, as a limitation, Markov Chains do not take into account explanatory variables within the deterioration model; the only variable considered is time (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). The current framework uses the Markov Chain process to model the skid deterioration.

Smith et al. (2016) used Utah data collected from 2005 – 2013 to evaluate the differences in deterioration trends of skid over time for different factors. An analysis of variance was performed to compare the effects of pavement age, month of testing, administrative region, AADT, and percentage of trucks on skid number deterioration rates. The researchers found that the deterioration variability of some pavements was lower than others, but it could not be concluded that different pavements had different skid deterioration rates.

In summary, different skid deterioration models have been developed in the previous decades. The main difference among them is the assumption of whether the skid reaches a final constant value or not. Some models use project-level data while others use network-level data. It is important to note that these models have not been used to link the impacts on road safety and the skid condition in a network.

2.6 PREVIOUS BENEFIT-COST RATIO ANALYSES OF SKID IMPROVEMENTS

There are different methods to estimate the economic benefits of a project, with the Benefit-Cost Ratio (BCR) being one of them. The BCR estimates the ratio between the value of benefits and the investment costs. Over the years, the BCR has been used to compare the impact of transportation projects (Transportation Economics Committee of TRB, 2016), and from 2010 to 2016, some studies have quantified the BCR of skid improvements, though with some limitations.

The Federal Highway Administration (2014) compiled analyses of pavement resurfacing treatments (applied to increase skid) at specific locations in different states. The comparisons of the reduction of crashes were performed on a case-by-case basis. The value of the benefit were calculated as the economic savings due to crash reductions, while the cost was equal to the total costs of the application of High Friction Surface Treatments (HFST). South Carolina DOT obtained BCR values ranging from 24 to 1 on curved roadway sections, while the Kentucky Transportation Cabinet applied the treatment in 26 curved roadway sections and found BCR values ranging from 6.2 to 1.9.

Brimley and Carlson (2012) analyzed the BCR of skid improvements for rural roads in Texas. This analysis included a sensitivity analysis of the potential crash reductions. The BCR value ranged from 60 to 20, but these values may have limited applicability since they were determined based on assumed crash reductions and life cycle duration of the skid treatments.

Finally, Long et al. (2014) performed an analysis of the Benefit-Cost ratio of skid improvements from an initial SN value of 14, 28, or 74 to a value of SN = 75. The results were a BCR of 39.6, 20.0, and 0.99 respectively. The study suggested that improvements of sections with low SN will yield a higher BCR compared to sections with higher SN. Likewise, the study suggested that improvements of sections with a SN value of 74 or above will have negligible impact on road safety. The study, however, had limitations because the life cycle of the skid treatment was assumed, and the skid deterioration over time (for the sections that are not treated) was not considered.

2.7 Summary of Literature Review

In summary, there is a proven relationship between crashes and low pavement friction. This relationship can be explained by the margin of safety factor, which is the difference between friction demand (given by the driving characteristics) and friction supply (given by the characteristics of the road). The expected crashes increase when the margin of safety decreases.

There are different skid thresholds that has been established based on the margin of safety and crash criteria. Likewise, there are different methods to measure skid; in the case of Texas, the test is conducted according to the ASTM E274 test. Historical information has been used by Long et al. (2014) to quantify the relationship of skid values and crash risks for Texas highways, using the concept of Crash Rate Ratio (CRR).

Different skid deterioration models have been developed in the last two decades, as well as Benefit-Cost Ratio analyses for skid improvements. However, the link between the skid deterioration models and the quantification of crash risks has not been explored. Moreover, there is no quantification of the economic benefits of improving skid at the network-level. This thesis fills this research gap by providing a framework to: 1) model skid deterioration using the Markov Chain process; 2) quantify the maintenance costs at the network-level for a maintenance threshold; 3) quantify the expected benefits of skid improvements at the network-level for a maintenance threshold; and 4) quantify the Benefit-Cost Ratio for different skid maintenance thresholds.

Chapter 3: Proposed Framework

The objective of this thesis is to develop a framework to estimate the Benefit-Cost Ratio of skid improvements in a network. The proposed framework is divided in three modules. The first module is the modeling of the skid resistance deterioration. In this module, historical skid data is used to predict future conditions using a Markov Chain model. The second module is the estimation of the maintenance cost. In this module, the different treatment types are analyzed in order to quantify the maintenance cost required for a specific skid threshold. The third module consists of the estimation of crash reduction by linking the skid improvements with expected crashes. Finally, the maintenance costs and crash reduction benefits are linked together in the Benefit-Cost Ratio analysis. The proposed framework is summarized in Figure 4.

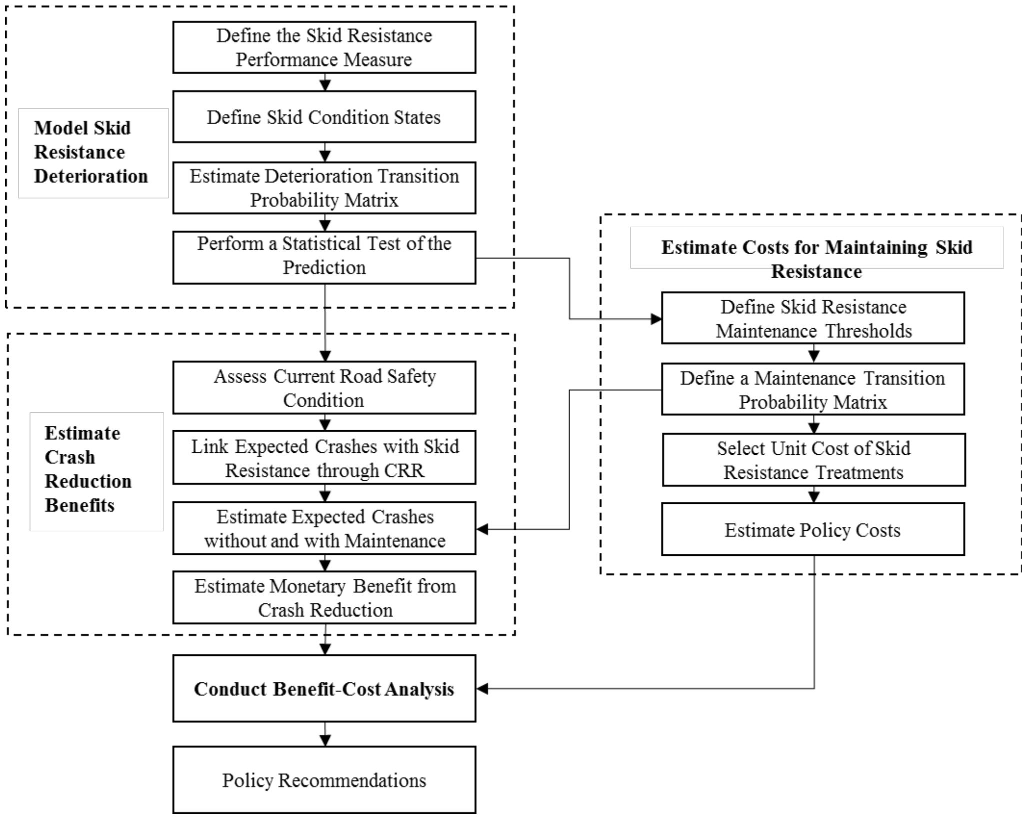


Figure 4: Framework for Developing the Benefit-Cost Ratio of Skid Improvements

The following is a summary of the chapters that discuss the modules that comprise this framework. Chapter 4 describes the Markov Chain principles and how this stochastic model can be applied for infrastructure deterioration. This chapter includes the different types of existing Markov Chains, the definition of a Markov Chain process, the estimation of the parameters of the model, and the estimation of future conditions of the system.

Chapter 5 describes the first module, that is, the development of the Markov Chain model. This chapter includes the data requirements for developing the model, the definition of the condition states, the estimation of the parameters for the Markov Chain process, the process to minimize the error in the model, and the statistical validation of the deterioration model.

Chapter 6 describes the second module, that is, the estimation of the maintenance costs. This chapter includes the definition of the maintenance policy and skid thresholds, the unit cost of the treatments, and the estimation of maintenance cost for different thresholds.

Chapter 7 describes the third module, that is, the estimation of crash reduction benefits. This chapter includes the estimation of expected crashes in the network, the expected reduction of crashes, and the economic estimation of this reduction.

Chapter 8 describes the development of the Benefit-Cost Ratio. Finally, Chapter 9 presents a case study using a portion of the skid database of the Austin District and Chapter 10 presents the major findings and conclusions of this thesis.

Chapter 4: Markov Chain Principles

Chapter 4 describes the Markov Chain principles and how this stochastic model can be applied for infrastructure deterioration. The chapter begins with the different types of existing Markov Chains and their advantages (4.1 – 4.2), and continues with the definition of a Markov Chain process (4.3), the estimation of the parameters of the model (4.4.), and the estimation of future skid condition of the network (4.5-4.6). The chapter finishes with recommendations for developing the deterioration model (4.7) and a summary (4.8).

4.1 Types of Markov Chains

There are different types of Markov Chains (MC), which are categorized by how the MC incorporates the time (discrete or continuous), the space (finite or infinite), and the behavior of the process over time (homogenous or heterogeneous) (Kallen, 2007) (Grinstead & Sell, 2012).

The difference between time-discrete and time-continuous MC is the amount of time elapsed between transitions. Time-discrete MC processes consist of the evolution of the condition state in the system over a set of discrete time-steps (or discrete-event steps). An example of a time-discrete MC is the evolution of pavement condition in the network from year to year. In contrast, time-continuous MC processes consist of the evolution of the condition state in the system over a set of continuous time. A theoretical example is the evolution of pavement condition measured instantaneously during a period of time.

The description of the space also creates two categories of MC. A finite-space MC process occurs when the number of possible condition states to which the system can transition are finite. For example, the SN score is an integer number within the range [1,100], which is a finite range. Infinite-space MC processes consist of an infinite number of state spaces (countable and/or non-countable) which could describe the system (Serfozo, 2009).

The changes in the transitions over time differentiates the time-homogenous MC from time-heterogeneous MC. Time-homogenous MC consists of processes where the probability of transition among condition states is constant over time; that is, the rate of 'change' in the system is constant over time. In contrast, time-heterogeneous MC presents different transition probabilities among condition states over time; that is, the rate of 'change' in the system could increase, decrease, or varies over time (Serfozo, 2009). For example, infrastructure deterioration can be considered as a time-heterogeneous process because, in general, the deterioration rates are a function of the infrastructure age (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015).

In general, infrastructure deterioration has been modeled as a finite-state time-discrete Markov chain process (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015) (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000) (Kallen, 2007) (Ortiz-Garcia, Costello, & Snaith, 2005) (Panthi, 2009) (Yang, 2004). The main reason is related to the condition data associated with the infrastructure. The measurements of the infrastructure condition (for example, indicators of pavement condition or bridge ratings) use a finite range that is usually countable. In the case of the SN, the score is an integer that ranges [1,100], being both countable and finite. Likewise, the data collection process results in a time-discrete MC. For example, the SN is not collected continuously but annually, and in some cases, the interval is bi-annual or longer (Wu, Zhang, Long, & Murphy, 2014). Specifically for pavement, it has been observed that deterioration models can be time-homogenous up to six years; for longer periods of time, the process becomes time-heterogeneous (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). Because the current scope of the framework is over a 4-year period, the finite-state, time-discrete, and time-homogenous approach is selected.

4.2 Advantages and Disadvantages of Finite-Space, Time-Discrete, and Time-Homogenous Markov Chain Models

The Markov Chain process has some advantages and disadvantages when used for modeling pavement or skid deterioration (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015) (Echaveguren, de Solminihac, & Chamorro, 2010) (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000) (Kallen, 2007) (Ortiz-Garcia, Costello, & Snaith, 2005) (Panthi, 2009) (Yang, 2004). The advantages of the Markov Chain processes are that:

- MC accounts for the uncertainty of the deterioration process because it is a stochastic model, representing an advantage over deterministic models.
- MC can incorporate new data easily.
- MC can model the performance trend even when the deterioration may be a non-linear process.
- MC depends only on the passage of time, minimizing the amount of data required for explanatory variables, which could be cumbersome for large networks.
- MC models have been used effectively to predict the skid condition of a network.
- MC predictions depend only in the current state of the system. This can be appropriate for skid modeling when the historical databases do not contain information about the age of the pavement or the date of last treatment applied.

The Markov chain process also has some disadvantages that are inherent to the method itself. Some of the potential advantages can be seen as limitations, too. The disadvantages of the Markov chain process are that:

- MC models depend only on the passage of time, while other explanatory variables of the deterioration (for example, AADT per lane, or climate) are not considered. Therefore, the Markov Chain does not provide guidance regarding the impacts of other factors.
- Time-homogenous MC models do not take into account the impact of the actual age of the pavement in the deterioration process.
- MC that have finite and countable states simplify the latent process of describing skid deterioration. Condition states are considered finite and countable when, in fact, the deterioration process is a continuous process. The same challenge is present in the definition of the SN value, which is discrete.
- MC do not consider the heterogeneity of the data collected; that is, the unobserved factors such as quality and repeatability of the measurements. In the case of the SN, the network-level test is collected for ½ miles on a 75 feet segment; this test is stored in PMIS as representative for the entire ½ mile section, though in fact, the SN value may vary due to flushing, raveling, patching changes in traffic and other factors.

Some solutions have been proposed to overcome these limitations. First, different deterioration models can be developed for different homogenous groups that take into account the explanatory variables. For example, the model can be developed for different traffic groups: low traffic, medium traffic, and high traffic. The same principle is applied in order to solve the non-time-homogenous behavior: the model can be developed for different groups with similar ages. As was previously stated, it has been established that, in general, the Markov chain process is time-homogenous for a period of 6 years for pavements; for that reason, the time-homogenous approach is used in this framework. Other approaches include the application of Poisson regressions to estimate the parameters or the development of ordered probit models (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015), but these methodologies are out of the scope of the present framework.

4.3 Definition of a Finite-Space, Time-Discrete and Time-Homogenous Markov Chain

In order to develop the deterioration model using the Markov Chain process, it is necessary to define three components: condition states, transition, and time step. The condition states are discrete groups that describe the condition, and are used to estimate the stochastic transition of the deterioration (Grinstead & Sell, 2012). The condition states are a set of finite conditions defined as: $S = \{s_1, s_2, \ldots , s_r\}$.

A transition is defined as the probability of changing from one state s_i to s_j over time, and it is denoted as p_{ij}. Likewise, the probability of remaining in the same state is also a transition, and in this case represents the probability of not changing its state condition over time; it is denoted as p_{ii}.

The time between transitions is denoted as the time grid or time step. For discrete-time Markov processes, the time grid is discrete and, most of the times, equidistant; that is, the time grid has the same separation (Kallen, 2007). The time is represented as an ordered set $\tau = \{t_0, t_1, \ldots, t_n\}$ where $t_0 < t_1 < \ldots < t_n$.

The Markov property condition states that the transition probability from one state to another depends only on the current condition and is independent of the previous condition states. Let X_t represent the stochastic process associated with the Markov chain, where $\{X(t) \mid t \in \tau\}$, and let k represent the time t, where $0 < k < n$. Formally, the Markov property condition can be stated as follows (Kallen, 2007):

$$\Pr\{X_{k+1} = x_{k+1} | X_k = x_k, X_{k-1} = x_{k-1}, \dots, X_1 = x_1, X_0 = x_0\} \\ = \Pr\{X_{k+1} = x_{k+1} | X_k = x_k\} \tag{4}$$

Where:

$\Pr\{X_{k+1} = x_{k+1} | X_k = x_k, X_{k-1} = x_{k-1}, \dots, X_1 = x_1, X_0 = x_0\}$ = Probability of reaching a condition state in the next step, given all the previous condition states of the system.

$\Pr\{X_{k+1} = x_{k+1} | X_k = x_k\}$ = Probability of reaching a condition state in the next step, given the current condition of the system only.

Time-homogenous MC are a special case of MC. Let i and j represent two condition states of S. The transition probability between condition states i and j in a time-homogenous Markov Chain can be formally described as (Kallen, 2007):

$$p_{ij} = \Pr\{X_{k+1} = j | X_k = i\} = \Pr\{X_1 = j | X_0 = i\} \tag{5}$$

Where:

p_{ij} = Transition probability from state i to state j.

$\Pr\{X_{k+1} = j | X_k = i\}$ = Probability of reaching condition state j at time $k+1$, given that the condition state at time k is i.

$\Pr\{X_1 = j | X_0 = i\}$ = Probability of reaching condition state j at time 1, given that the initial condition state is i.

All the possible transitions among condition states can be arranged in a matrix called the Transition Probability Matrix (TPM) and denoted as ***P***. The TPM is square with r number of columns and rows, and each entry $ijth$ represents the p_{ij}. Equation 6 presents the structure of the TPM**.**

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{bmatrix} \tag{6}$$

Because the entries of the TPM are the transition probabilities, the value of p_{ij} is $0 \leq p_{ij} \leq 1$. Likewise, the rows represent the probability of transitioning from or remaining at state i; thus $\sum_{j=1}^{r} p_{ij} = 1$. When all the values of the TPM are greater than zero, the TPM is called Regular MC. When at least one of the condition states has a transition probability of 1 (that is, if one of the transition probabilities p_{ij} = 1), the MC is denominated as absorbing MC. Likewise, the condition states with the transition probability of 1 are called absorbing states (Grinstead & Sell, 2012). Absorbing states represent condition states that, once the state is reached, will be impossible for the system to leave that condition.

According to Kallen (2007), the Markov Chain should have, at least, the following two characteristics in order to model infrastructure deterioration. First, the condition states must represent the different conditions of the system, and they must be strictly ordered from the best condition to lower conditions. In other words, the condition states must be ordered to represent the deterioration in a logical way. Second, the condition of the system must progress through the condition states. This means that the overall system condition must deteriorate over time until the last state or failure is produced (Yang, 2004).

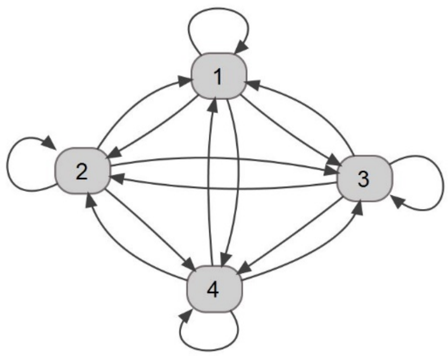
Based on the two aforementioned characteristics, two types of MC have been commonly used to model deterioration: progressive MC and sequential MC. Progressive MC represents TPMs where there is no maintenance, and, thus, there are no transitions from low condition states to better states (Yang, 2004). Sequential Markov chains follow the same principle of no improvement, but they impose an additional restriction: transitions from state to state must be sequential. In other words, condition states cannot be skipped (Kallen, 2007). Sequential Markov chains are special representations of the binomial distribution for each condition state. In both cases, the processes are not regular (that is, TPMs contain at least one zero) and have absorbing condition states in the worse condition. Equation 7 and Equation 8 present TPMs for a Progressive MC and Sequential MC respectively.

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ 0 & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{7}$$

$$\boldsymbol{P} = \begin{bmatrix} 1-p_{12} & p_{12} & 0 & \cdots & 0 \\ 0 & 1-p_{23} & p_{23} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \tag{8}$$

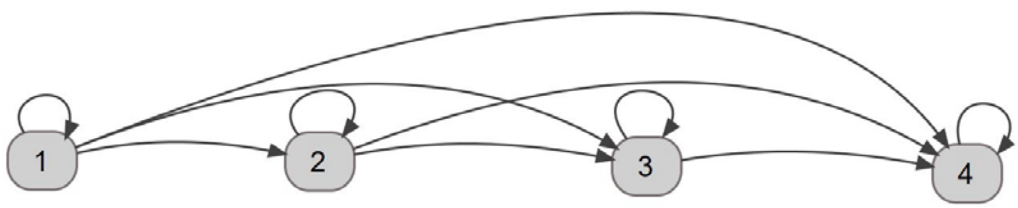
There is not a defined rule of whether Progressive MC or Sequential MC is the best model because the TPM depends on 1) the deterioration process and 2) the definition of the condition states. The best approach is to model the process using a Progressive MC (which is the general case), and if the data calibration follows Sequential MC, the TPM can be adapted. This approach is used in this framework.

Another way of representing the Markov chain process is through the Markov Rate Diagrams (MRD). The MRD are graphical representations of the condition states, with arrows indicating the transition probabilities that are different than zero. Loops around a condition state represent the possibility to remain in the same condition state in one time step. Figure 5 presents examples of the MRD for a Regular, Progressive, and Sequential Markov chain with four condition states.



$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix}$$

a) Regular Markov Chain



$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ 0 & p_{22} & p_{23} & p_{24} \\ 0 & 0 & p_{33} & p_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

b) Progressive Markov Chain

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & 1 - p_{11} & 0 & 0 \\ 0 & p_{22} & 1 - p_{22} & 0 \\ 0 & 0 & p_{33} & 1 - p_{33} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

c) Sequential Markov Chain

Figure 5: Example of a Markov Rate Diagram and Transition Probability Matrix for a Four-State a) Regular Markov Chain, b) Progressive Markov Chain, and c) Sequential Markov Chain.

4.4 Estimation of Transition Probability Matrix

One method used to estimate the entries of the TPM is the "count proportions" method (Equation 9). It uses a sample of historical data as a statistical estimation of the real parameter p_{ij} for the TPM (Panthi, 2009). It is important to note that the value of $\hat{p}_{ij}$ will tend to the real p_{ij} for larger samples, and for that reason, more data points will increase the capability of prediction of the model.

$$\hat{p}_{ij} = \frac{n_{ij}}{\sum_{j=0}^{r} n_{ij}} \tag{9}$$

Where:

$\hat{p}_{ij}$ = Estimated Transition probability from state i to state j.

n_{ij} = The number of observed transitions from state i to state j.

r = The total number of condition states.

$\sum_{j=0}^{r} n_{ij}$ = Total number of transitions originated from state i.

4.5 Estimation of the Future Condition of the System

The future condition of the system depends of the initial (or current) condition of the system and the TPM. The condition of the system is denoted by the vector $\boldsymbol{u}$ which contains the probabilities of the system being in each condition state at a given time. The initial condition is denoted as $\boldsymbol{u}_0$. The vector $\boldsymbol{u}$ has r non-negative entries, and $\sum_{i=0}^{r} u_k = 1$ (Grinstead & Sell, 2012). Equation 10 presents the estimation of the future condition of the system at time k as a function of the initial condition and the transition probability matrix.

$$\boldsymbol{u}_k = \boldsymbol{u}_0 \boldsymbol{P}^k \tag{10}$$

Where:

$\boldsymbol{u}_k$ = Estimated system condition vector at time step k.

$\boldsymbol{u}_0$ = Initial condition vector.

$\boldsymbol{P}$ = Deterioration Transition Probability Matrix.

k = Time step.

4.6 Optimization of the Transition Probability Matrix

In order to develop a model that is robust, different techniques have been developed in order to minimize the error between the prediction and the observed values. Non-linear programming has been used in order to estimate the parameters in deterioration models where the time is the explanatory variable and the state is the dependent variable (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). Likewise, non-linear programming has been used to minimize the differences between the prediction and observed values in MC processes for bridges and pavements (Yang, 2004) (Panthi, 2009) (Ortiz-Garcia, Costello, & Snaith, 2005). The objective function can be the sum of the absolute difference (Equation 11) or the squared difference (Equation 12). These objectives functions are minimized using non-linear programming techniques.

$$Min \sum_{t=1}^{n}\sum_{i=1}^{r}\left|\boldsymbol{u}_{t,i} - \boldsymbol{\hat{u}}_{t,i}\right| \tag{11}$$

Where:

$n =$ Total number of transition periods.

$r =$ Total number of condition states in the model.

$\boldsymbol{u}_{t,i} =$ Observed frequencies in state *i* at time *t*.

$\boldsymbol{\hat{u}}_{t,i} =$ Estimated frequencies in state *i* at time *t*.

$$Min \sum_{t=1}^{n}\sum_{i=1}^{r}\left(\boldsymbol{u}_{t,i} - \boldsymbol{\hat{u}}_{t,i}\right)^2 \tag{12}$$

Where:

$n =$ Total number of transition periods.

$r =$ Total number of condition states in the model.

$\boldsymbol{u}_{t,i} =$ Observed condition of state *i* at time *t*.

$\boldsymbol{\hat{u}}_{t,i} =$ Estimated condition of state *i* at time *t*.

4.7 Develop the Transition Probability Matrix For Heterogeneous Groups

As previously discussed, Markov Chains do not take into account explanatory variables (besides time) explicitly. One of the solutions for overcoming this limitation is creating homogenous groups where the data has similar attributes. The purpose is to reduce the variability in the explanatory variables, allowing the TPM to capture the deterioration process for specific conditions. However, this requires more data and, at the same time, reduces the scope of the application of the model (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015) (Yang, 2004). In general, the following categories have been used to create groups of similar characteristics for skid deterioration and pavement deterioration (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015) (Yang, 2004) (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000) (Wu, Zhang, Long, & Murphy, 2014) (Rezaei & Masad, 2013) (Pratt, et al., 2014) (Smith, Knighton, & Guthrie, 2016). Depending on the data available and the scope of the analysis, these categories can be used to develop different TPMs that could lead to different Benefit-Cost Ratios:

- AADT per lane,
- Locality and/or climate,
- Curves or non-tangent sections,
- Age of the pavement, and
- Quality of the aggregates used for construction, if available.

4.8 SUMMARY

Markov Chains are a stochastic processes aimed to capture the evolution of the system condition. There are different types of MC processes, but the most commonly used to model infrastructure deterioration are the finite-state, time-discrete and time-homogenous MC; for that reason, this approach is used in this thesis. The main advantage of the MC is the predictive power using only historical data, but this also is a limitation because it does not incorporate other explanatory variables.

At least two conditions are required in order to model the deterioration process properly: the condition states must be ordered from the best condition to the lowest condition, and the system must transition from the best condition to the lowest condition. Progressive TPMs and sequential TPMs are two types of TPMs that fulfill these conditions.

The estimation of the parameters of the TPMs can be obtained using historical data. After the estimation, non-linear optimization processes has been developed in order to reduce the error between the prediction and the observed values. Finally, one option to explore the impact of explanatory variables in the MC deterioration process is to group pavement segments with similar attributes and perform the analysis. However, this also creates the need for more data input.

Chapter 5: Model Skid Resistance Deterioration

Chapter 5 describes the development of the Markov Chain (MC) deterioration model. This chapter begins with the data requirements for developing the model (5.1), the definition of the condition states (5.2), the estimation of the parameters for the Markov Chain process (5.3), and the statistical validation of the deterioration model (5.4). The chapter finishes with summary (5.5). The framework of the development of the skid resistance deterioration model is summarized in Figure 6.

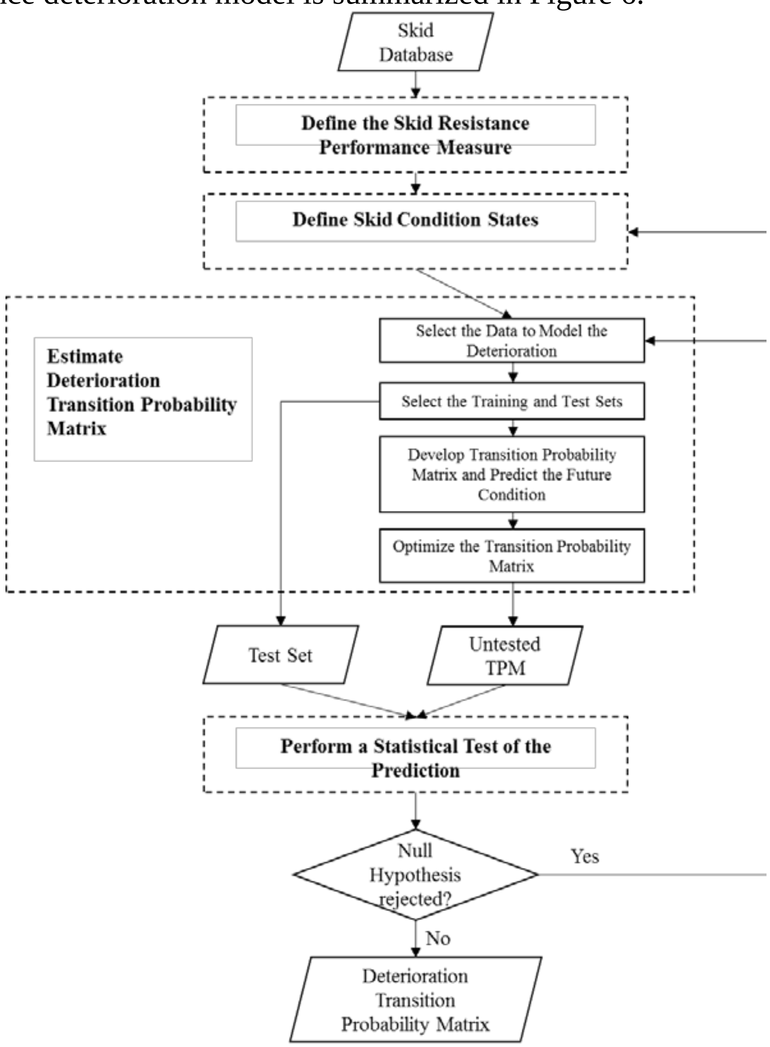


Figure 6: Framework for Developing the Skid Resistance Deterioration Model

As Figure 6 shows, the process starts with the skid database. Next, based on historical data and technical criteria, the skid condition states are defined. The states are the foundation of the MC process and are used through the rest of the analysis.

The next step is the estimation of the Transition Probability Matrix (TPM) for the deterioration model. The output is an optimized TPM and a test set that is used to determine if the model is able to predict the future condition of the network or not. This is done through the Chi-Square Goodness-of-Fit statistical test. There are two possible outcomes of this test: the TPM is rejected (that is, the differences between the observed and predicted values are too large) or the TPM is accepted (that is, the TPM can predict the future condition of the network with an acceptable accuracy). If the TPM is rejected, it is necessary to return to the definition of the condition states and the selection of the data to develop the model. In contrast, if the TPM is accepted, the model can be used for the next modules of the analysis (estimation of the maintenance cost and expected crash reductions).

5.1 Select Skid Resistance Performance Measure

The objective of this step is to select and define the skid resistance data that is consistent in the database. In order to conduct the Benefit-Cost Ratio analysis, it is very important to define the method in which skid is measured, and be consistent with it through the analysis. As is presented in subchapter 2.2 Method to Measure Skid, there are different methods and parameters that could cause changes to the value of skid resistance. It is necessary to perform the analysis with consistent data; that is, skid data must be in the same units in the dataset. Likewise, if other sources of information are used to support the analysis, these must have the same performance measure as the dataset before being used in the analysis.

5.2 Define Skid Condition States

The objective of this step is to define the number of skid condition states and their boundaries. The definition of the number of condition states and their thresholds depend on the problem to be modeled; there are no strict rules to define them. However, based on previous experiences, the following recommendations have been used to define the condition states (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000) (Yang, 2004) (Kallen, 2007) (Panthi, 2009):

- **Condition states must be ordered:** The condition states represent the different conditions that the infrastructure could have. Thus, the condition states must be ordered to represent the deterioration in a logical way. This also means that the condition states need to have contiguous boundaries.
- **Local Standards:** If an agency has established thresholds to define conditions, these thresholds can be used to describe the conditions. In the case of the skid, it is also important that thresholds have consistent measurement units and test parameters.
- **Availability of Data and Minimum Frequencies:** The condition states must have enough data points to estimate the TPMs properly; that is, all the condition states must have a minimum of skid observations (frequencies). If a condition state has relatively low frequencies (for example, a condition state with only 1 observation), the uncertainty of the transition probability estimation will increase.
- **Representativeness of the Deterioration Process:** The condition states must represent conditions that are possible, and that are representative of the deterioration.

- **Level of Disaggregation of the Analysis:** In the case that the researcher has interest in specific phases of the deterioration, the condition states can be disaggregated in order to capture specific transitions with more detail. However, the limitation is the availability of data; it must be guaranteed that the minimum frequencies are achieved in each condition state.

5.3 ESTIMATE DETERIORATION TRANSITION PROBABILITY MATRIX

The objective of this step is to estimate the transition probabilities among the different condition states defined in the previous subchapter 5.2 Define Skid Condition States. The output is a TPM that is cross-validated with the Chi-Squared Goodness-of-Fit statistical test.

5.3.1 Select the Data to Model the Deterioration

In order to model the deterioration of the skid resistance, it is necessary to build a sample that is a subset of the complete network. The objective of this sample is to develop the deterioration model using relevant data that will capture the "natural" deterioration if no treatment is applied.

In the case of skid, there are three ways to select only the sections that have a natural deterioration process (that is, sections that have not received any treatment). One way is by selecting a limited number of "experimental" sections in the network that will be monitored over a period of time and where treatments are not applied. The sections are divided in two groups in order to have a control of the deterioration (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000). This method has the advantage of capturing, in an experimental setting, the deterioration of skid; however, this could be expensive for an agency. Another way is to exclude from the analysis the sections that have received a treatment. However, not all the pavement databases have available information about the historical treatments applied in all the sections (Panthi, 2009). The last option is to use skid data itself: if the historical treatment information is not available, the researcher should select only the sections that have a natural trend of deterioration (that is, the SN drops continually). It is important to note that some increases in SN are due to uncertainty in the measurements and are not related to actual maintenance improvements (Corsello, 1993); therefore, it is important to know the uncertainty of the skid measurements. For example, a pavement with an real SN of 41 during two consecutive years could have a measured SN of 40 in year 1, and SN of 42 in year 2. This increase of 2 SN does not correspond to surface improvements, but it is due to the variability in the measurements. In this framework, the standard deviation estimated by the ASTM for repeated SN measurements is used as the criterion to determine SN changes due to measurement variability (ASTM International, 2015).

Commonly, sections with missing values are discarded for the analysis; however, if the missing values are not completely at random (that is, if there is correlation between the missing sections and the skid values), there could be a bias in the development of the model if the missing values are discarded (Raghunathan, 2015). For example, in the case of Texas, the skid resistance is collected annually from 50 percent of the Interstate Highways and 25 percent of other parts of the network (Long, Wu, Zhang, & Murphy, 2014). It is likely that a higher amount of missing values are present in state roads compared to IH, creating a bias of the available information toward highways.

An additional criterion that can be used to select the data is the homogeneity in explanatory variables of skid deterioration, as is described in subchapter 4.7 Develop the Transition Probability Matrix For Heterogeneous Groups. This could include AADT per lane, locality and/or climate, curves, age of the pavement, or quality of the aggregates used for construction, if available.

Finally, the attributes of the data available can influence the model development. The frequency of collection (for example, annual or bi-annual), quality of the data collected (for example, if data has different formats), and coverage of the data (for example, 20 percent of the network every year) determines the characteristics of the deterioration model and the representativeness of the network sample. For example, when only bi-annual data is available, the model would have a time step of two years.

5.3.2 Select the Training and Test Sets

The objective of this step is to select the training set and test set in order to test if the prediction is significantly accurate. The training set is data that is used to develop the model, while the test set is data that is used to validate the model. There are different methods to cross-validate the models, with the most commonly used being the holdout, k-fold cross validation, random subsampling, and bootstrap (Kohavi, 1995) (Rai, 2011). Other methods have been developed in the last years, such as "information criteria based methods" and the Minimum Description Length (MDL) method; however, high computational capabilities are required to develop them and are therefore not considered in the present framework.

The holdout procedure consists of dividing the data set into two subsets, usually of 2/3 and 1/3 proportions. The largest subset is called the training dataset and is used to develop the model. The remaining set (test set) is used to validate the model developed (Figure 7). One of the advantages is that this method requires less computational time and is easy to implement, but the disadvantage is that the estimation is pessimist because the training set uses less data (a portion is used for the test set only). The k-fold cross validation uses the same principle of the holdout method, but instead of dividing the set once, the set is subdivided *k* times. Each subset is used for training and the remaining for testing (Figure 8); thus, the whole dataset is used to develop and validate the model. Random subsampling consists of k subsamples (training sets and test sets) that are selected randomly. The size of the training sets is αN where $0 < \alpha < 1$ and N is the total sample set. Usually α is 0.1 and k is 10. The model selected is the one with the smallest average validation error (Figure 9). The Bootstrap method is a modification of the Random Subsampling method. It selects a defined number of elements as "examples," and any element of the dataset can be selected multiple times in different examples. Next, each example is used as a training set and the rest of the examples are used as the test set.

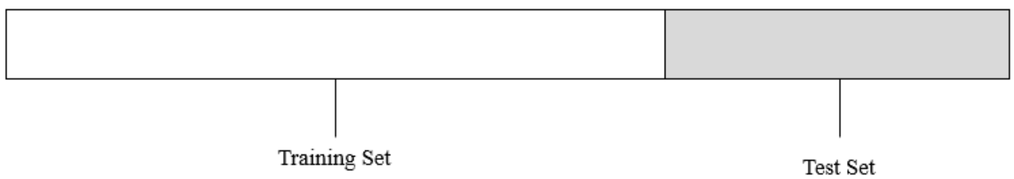


Figure 7: Example of the Holdout Cross-validation

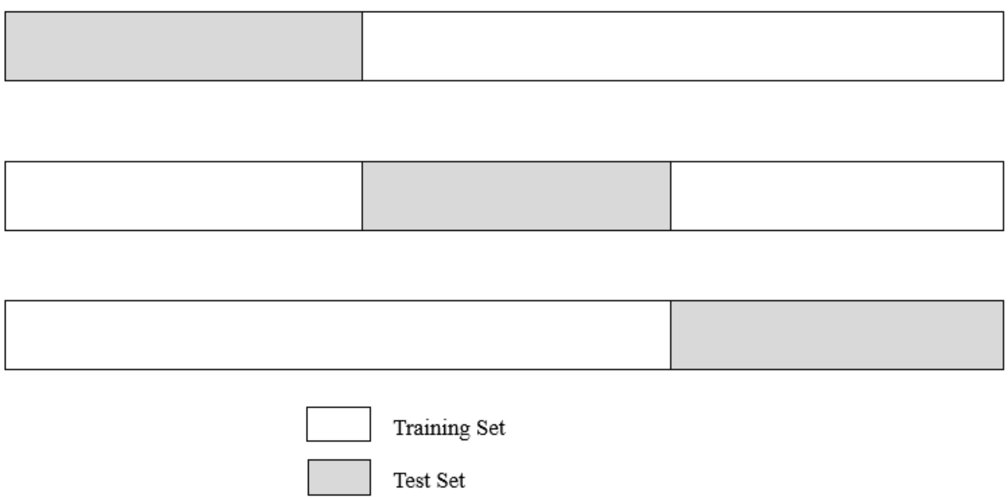


Figure 8: Example of the K-Fold Cross-validation for k=3

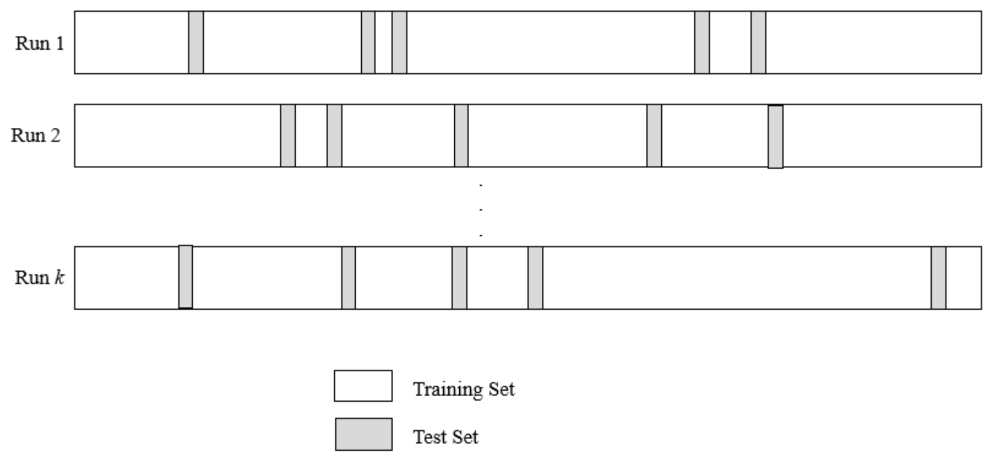


Figure 9: Example of the Random Sampling Cross-validation for *k* Subsampling

The selection of the training and test sets depends on the amount of data available and computer capabilities (Rai, 2011). Nevertheless, it is very important to perform the cross-validation using at least one of the aforementioned methods; this allows the researcher to corroborate the prediction of the network deterioration. The present framework uses the holdout method.

5.3.3 Develop Transition Probability Matrix and Predict the Future Condition

The training dataset is used to develop the Transition Probability Matrix (TPM). As explained in subchapter 4.4 Estimation of Transition Probability Matrix, the "Count Proportions" method can be used to estimate the parameters of the TPM (Equation 6). In the case of data from multiple time steps (for example, skid data for multiple years), the TPM of the time-homogenous MC can be estimated as the "counting proportions" of the transitions for all the time steps (Equation 13). This is possible because, for a time-homogenous MC, the transitions probabilities are independent of time.

$$\hat{p}_{ij} = \frac{\sum_{t=1}^{n} N_{t,ij}}{\sum_{t=1}^{n} \sum_{j=0}^{r} N_{t,ij}} \tag{13}$$

Where:

$\hat{p}_{ij}$ = Estimated annual transition probability from the *i*th to the *j*th condition state.

$N_{ij,t}$ = The number of observed transition from the *i*th to the *j*th condition state, for year *t*.

n = Total number of years observed.

r = Total number of condition states.

Subsequently, the TPM is used to estimate the future condition of the network, using as a base year the first year of available data. The estimation is done as described in subchapter 4.5 Estimation of the Future Condition of the System, Equation 10.

5.3.4 Optimize the Transition Probability Matrix

As described in subchapter 4.6 Optimization of the Transition Probability Matrix, it is required to minimize the error of the TPM estimated in the previous step. This is done by non-linear programing reducing the differences between the observed (historical) values and the estimated prediction.

For this framework, the objective function selected is the sum of squared errors (SSE) (Ortiz-Garcia, Costello, & Snaith, 2005). Equation 14 presents the formula to estimate the relative error, while Equation 15 presents the formula to estimate the Sum of Squared Errors (SSE) (Weiss, 2008).

$$Er_{t,i} = \frac{(\boldsymbol{u}_{t,i} - \widehat{\boldsymbol{u}}_{t,i})}{\boldsymbol{u}_{t,i}} \tag{14}$$

Where:

$Er_{t,i}$ = Relative error for year t and condition state i.

t = Year t.

i = Condition state i.

$\boldsymbol{u}_{t,i}$ = Observed number of sections in state i at time t.

$\widehat{\boldsymbol{u}}_{t,i}$ = Estimated number of sections in state i at time t.

$$SSE = \sum_{t=1}^{n}\sum_{i=1}^{r} Er_{t,i} \tag{15}$$

Where:

SSE = Sum of Squared Errors of the prediction.

$Er_{t,i}$ = Relative error for year t and condition state i.

n = Total number of years observed.

r = Total number of condition states.

The SSE can be minimized using the non-linear optimization process with restrictions over the values of p_{ij}. These restrictions are applied in order to comply with the properties of the MC TPMs; that is, $0 \leq p_{ij} \leq 1$ and $\sum_{j=1}^{r} p_{ij} = 1$, where r is the total number of condition states (see subchapter 4.3 Definition of a Finite-Space, Time-Discrete and Time-Homogenous Markov Chain). The following are the restrictions of the optimization for a Progressive Markov Chain TPM (Yang, 2004) (Kallen, 2007) (Panthi, 2009):

1. **Values in the diagonal of the TPM (except for the lowest condition state) range [0,1):**

   That is, $0 \leq p_{ii} < 1$. In the case that $p_{ii} = 0$, this means that in one time step all the frequencies move from condition state *i* to other condition states, which is possible. In contrast, $p_{ii} \neq 1$ because this would mean the condition state *i* is an absorbing state, implying no deterioration; in other words, the system does not transition to a lower condition state after condition state i.

2. **The lowest condition state of the TPM is an absorbing state:**

   That is, $p_{ii} = 1$ for the lowest condition state. This restriction implies that once the system reaches this condition state, the system does not transition to any other state.

3. **Values below the diagonal are zero:**

   That is, $p_{ij} = 0$ for $j < i$. All the values below the diagonal represent improvements in the condition of the system, which does not happen in a deterioration process unless maintenance is applied.

4. **Values above the diagonal of the TPM range between [0,1]:**

   That is, $0 \leq p_{ij} \leq 1$ for $j > i$. This restriction represents the fact that the system can deteriorate from condition state i to lower condition states.

5. **The sum of the rows of the TPM are equal to 1:**

   That is, $\sum_{j=1}^{r} p_{ij} = 1$ where r represents the total number of states. This restriction enforces that 100 percent of the frequencies of the condition state i either 1) remain in the same condition state, or 2) transition to another condition state. If the sum of the rows are not equal to 1, the TPM would no longer represent a MC process.

The TPM can also be modeled as a Sequential Markov Chain TPM. As is explained in subchapter 4.3, Sequential TPMs are common in models in which the system must pass through all the condition states before reaching the lowest condition (for example, bridge ratings in which the bridge cannot skip a condition state; condition must transition through all of the states before failure) (Kallen, 2007). In the case of skid resistance this is not necessarily true; the skid deterioration is a function of the time step and the condition states defined (for example, aggregated condition states vs multiple condition states). For long time steps in data collection, it is possible that the system transitions through some states, but these transitions are not observed. Likewise, in the case of multiple condition states, it could happen that the deterioration is faster than the level of disaggregation of the condition states. Notwithstanding, a combination of these two factors could produce a Sequential process. The following are the restrictions for the optimization for a Sequential Markov Chain TPM (Yang, 2004) (Kallen, 2007) (Panthi, 2009):

1. **Values in the diagonal of the TPM (except for the lowest condition state) range [0,1):**

   That is, $0 \leq p_{ii} < 1$. Similar to Progressive TPMs, in the case that $p_{ii} = 0$ this means that in one time step all the frequencies move from condition state i to other condition states, which is possible. In contrast, $p_{ii} \neq 1$

because this would mean the condition state i is an absorbing state, implying no deterioration; in other words, the system does not transition to a lower condition state after condition state i.

2. **The lowest condition state of the TPM is an absorbing state:**

   That is, $p_{ii} = 1$ for the lowest condition state. Similar to Progressive TPMs, this restriction implies that once the system reaches this condition state the system does not transition to any other state.

3. **The transition probability of the next condition state is 1- *p*:**

   That is, $p_{ij} = 1 - p_{ii}$ for $j = i + 1$. This restriction represents the fact that, in a Sequential MC, the only possible transition is to the next state. Likewise, it ensures that the sum of the rows is equal to one.

4. **The transition probability is zero elsewhere:**

   That is, $p_{ij} = 0$ for $j \neq \{i, i + 1\}$. This restriction represents the fact that 1) there is no possibility that the system skips a condition state; and 2) the system cannot transition to better condition states unless maintenance is applied.

5.4 PERFORM A STATISTICAL TEST OF THE PREDICTION

The objective of this step is to perform a statistical test to determine whether the optimized TPM predicts the future condition of the network. The statistical test used is the Chi-Square Goodness-of-Fit Test (Weiss, 2008). The test is applied twice: first, it is applied for the training set, and then it is applied for the test set. Both tests must be successful before continuing to the next modules.

The inferences of the Chi-Square test are based on the Chi-Square distribution. The Chi-Square value (χ^2) measures the relative difference between the observed and expected frequencies for categorical or discrete quantitative variables with a finite number of possible values (which is the case of the finite-space Markov Chain). This distribution is composed of infinite curves that describe the probabilities of the values of the statistic χ^2. The distribution is a function of the Degrees of Freedom (DF), which is the number of variables involved in the analysis minus one. When the number of DF is large, the distribution of the χ^2 tends to a normal distribution (Weiss, 2008).

The Chi-Square test has some restrictions because the exact distribution of χ^2 is continuous. Therefore, when the frequencies are low, there is an increased error between the exact distribution and the approximation for discrete variables. For that reason, it is recommended that all the frequencies are above zero (that is, there is no condition state with a zero observations at any time step), and no more than 20 percent of the expected frequencies is below five (Cochran, 1952) (Weiss, 2008). Equation 16 presents the formula to estimate the χ^2 for the skid deterioration model.

$$\chi^2 = \sum_{t=1}^{n}\sum_{i=1}^{r}\frac{(\boldsymbol{u}_{t,i} - \hat{\boldsymbol{u}}_{t,i})^2}{\boldsymbol{u}_{t,i}} \tag{16}$$

Where: χ^2 = Chi-Square value.

n = Total number of years observed.

r = Total number of condition states.

t = Year *t*.

i = Condition state *i*.

$\boldsymbol{u}_{t,i}$ = Observed number of sections in state *i* at time *t*.

$\hat{\boldsymbol{u}}_{t,i}$ = Estimated number of sections in state *i* at time *t*.

According to Weiss (2008), the following is the process of the Chi-Square Test:

1. **Select Null Hypothesis:** Select the null hypothesis (H_0) and the alternative hypothesis (H_a) for the test. The H_0 is that the differences between the observed frequencies and the estimated frequencies with the model are not significant.
2. **Calculate the Expected Frequency:** The expected frequency is the estimation of the condition for different years, using Equation 10.
3. **Check if the restrictions are not violated:** All the frequencies must be above zero and no more than 20 percent of the expected frequencies is below five.
4. **Decide the significant value of α:** The value of α represents the probability of rejecting the null hypothesis when is true; usually its value is 0.05.
5. **Compute the value of χ^2:** The value of χ^2 is computed using Equation 16.
6. **Compare results with the critical value:** For a specific number of Degrees of Freedom (DF), the Chi-Square distribution has a critical value for the defined α. If χ^2 is higher than this value, it means that there are significant differences between the observed frequencies and the predictions, and thus the MC model does not predict the future condition of the network (and therefore, it did not capture the deterioration process). Another approach is to estimate the probability p of obtaining the χ^2 under the assumption that H_0 is true. In this case, if $p \leq \alpha$, it means that there are significant differences between the observed frequencies and the

predictions, and again, the MC model does not predict the future condition of the network (and therefore, it did not capture the deterioration process).

The test must be applied to the training set first. If the null hypothesis (H_0) is rejected, it is necessary to develop the model again. If H_0 is not rejected, the test is applied to the test set. This is done to estimate if the model predicts the future condition for a set of new data. If H_0 is rejected, it is necessary to build the model again. If H_0 is not rejected, the deterioration model can be used to estimate the maintenance costs and benefits of improving skid.

Low frequencies can affect the estimation of χ^2. To overcome this limitation, more data can be collected in order to increase the number of pavement sections in each of the defined condition states. Likewise, condition states with low frequencies can be aggregated in order to increase the expected frequencies in each state.

It could happen that the data to be modeled does not follow a time-homogenous MC process, especially if the number of time steps cover more than five years (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). In this case, a shorter analysis period can be selected for the development of the TPM. Finally, the deterioration process can have high variability if it is a heterogeneous group with different attributes (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). In this case, a solution is to create specific groups with homogenous characteristics in order to reduce the variability in potential explanatory variables, as it is explained in subchapter 4.7 Develop the Transition Probability Matrix For Heterogeneous Groups.

5.5 SUMMARY

This chapter describes the framework to develop the Markov Chain model for skid deterioration. It is important to use consistent data through the analysis and define the condition states using established thresholds and data available as criteria. The process of creation of the TPMs for the MC process is an iterative process. First, a portion of the data is selected for training the model, and the rest is used for testing the prediction. Then, the TPM is estimated and optimized in order to reduce errors in the prediction. Finally, the Chi-Square Goodness-of-Fit statistical test is applied to the prediction in order to corroborate that the model is capturing the deterioration. If this is not the case, the process of defining the TPMs starts again.

Chapter 6: Estimate Costs for Maintaining Skid Resistance

Chapter 6 describes the process for estimating the maintenance costs for different minimum skid thresholds. This chapter begins with the definition of the maintenance policy and thresholds (6.1), and continues with the development of the Maintenance Transition Probability Matrix (6.2), the unit cost of the treatments (6.3), and the estimation of maintenance cost for different thresholds (6.4). Figure 10 presents the framework for estimating costs of maintaining the skid resistance.

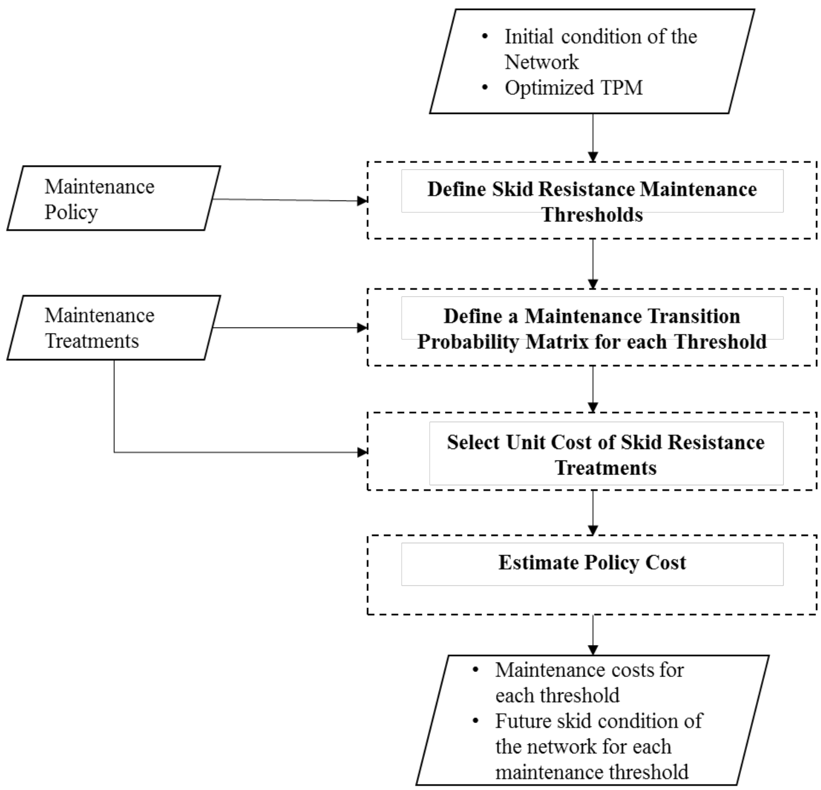


Figure 10: Framework for Estimating the Skid Resistance Maintenance Costs

This module receives as an input the initial condition of the network (skid condition in the base year) and the TPM of the deterioration model. Based on a maintenance policy, the minimum skid thresholds are defined. These skid thresholds are used to create a Maintenance Transition Probability Matrix for each threshold. The Maintenance Matrix is used to estimate the future skid condition of the network under maintenance. Subsequently, the unit costs for the maintenance treatments are established, and the total maintenance costs are estimated. The estimated future condition of the network under maintenance is used in the next module.

6.1 DEFINE SKID RESISTANCE MAINTENANCE THRESHOLDS

The objective of this step is to define the minimum skid threshold that is applied to the network. Since there are different maintenance policies that can be applied, there could be different costs and different impacts to the network. However, as it is mentioned in the Scope of this framework, this study does not include the quantification nor the optimization of different maintenance policies. This framework selects one maintenance policy and estimates the associated costs based on the deterioration model developed.

The following is an overview of the different maintenance policies that are applied on infrastructure systems (Uddin, Hudson, & Haas, 2013):

- **Do Nothing Policy:** No maintenance is applied to the system, and the natural deterioration is allowed to occur (no maintenance is performed).
- **Routine Maintenance Policy:** Maintenance is applied at a periodic frequency in order to keep the service level consistent.
- **Critical Maintenance Policy:** Maintenance is applied to avoid imminent failures, and as a response to special events (for example, natural disasters or accidents).

- **Scheduled M, R & R Policy:** Maintenance, rehabilitation, and replacement are scheduled based on historical information that has been analyzed.
- **Condition-Responsive M, R & R Policy:** Maintenance is triggered when the performance of the system (or of the components of the system) achieves a specified threshold. For example, a pavement section is treated if it has a SN below the maintenance threshold.

In general, the management of infrastructure systems requires the combination of all the different policies. In this framework, the do-nothing and condition-responsive policies are used in order to model the base case (do-nothing policy) and the maintenance scenario (condition-responsive policy). The estimation of the number of crashes expected if the natural deterioration is allowed in the network is based on the do-nothing policy, while the estimation of crash reduction and maintenance costs are based on the condition-responsive policy.

For the condition-responsive policy, it is necessary to define the thresholds that will trigger the maintenance actions. In this framework, the thresholds are defined as the maintenance goals. The maintenance goal is defined as the minimum value of SN in the network during the analysis period. In other words, when a section reaches a SN below the goal, the section is treated in order to improve the SN.

It is important to note that the condition-responsive policy is an idealization of skid management. First, it assumes that there are no economic constraints to treating all the sections that required treatment. Second, it assumes that the network-level skid is representative of the pavement section, which is not always true. In the case of Texas, network-level skid is measured at the beginning of pavement sections; therefore, the skid condition in the rest of each section is not known. For these reasons, the current framework estimates the economic benefits at the network-level, and detailed analysis should be performed at the project level for specific cases.

6.2 Define a Maintenance Transition Probability Matrix for Each Threshold

The objective of this step is to integrate the policy previously defined in the estimation of the future condition of the network. This is achieved by developing the Maintenance Transition Probability Matrix, which is denominated ***M***. The matrix ***M*** describes the transition probabilities among condition states after a treatment is applied. Different treatments can cause different transition probabilities and, by consequence, different values of ***M***.

The best way to estimate ***M*** is using historical quantitative data before and after a treatment is applied (Uddin, Hudson, & Haas, 2013). In the case of the skid, this is done by measuring the SN before and after a treatment. Next, as happens with the development of the TPMs, the "count proportions" method can be used to estimate the transition probabilities for ***M***. Though the aforementioned procedure is a costly method for an agency (because requires them to measure the SN before and after a treatment), the "count proportions" method for treatments was used in the past with successful results (Panthi, 2009). Furthermore, the same process can be applied to identify the impacts of other non-skid treatments that have an impact on skid and that are applied on a regular basis. If this information is not available, historical data or assumptions about the improvement of the skid after a treatment are required (Brimley & Carlson, 2012).

The matrix ***M*** is a square matrix, with the number of rows and columns being the total number of states of the MC. The inputs of ***M*** are also denominated performance jumps, because they represent the instantaneous "jumps" in the system after a treatment

(Panthi, 2009). In general, the maintenance matrix **M** has the following structure (Equation 17):

$$\boldsymbol{M} = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ m_{21} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ m_{r1} & m_{r2} & \cdots & 0 \end{bmatrix} \tag{17}$$

where:

$m_{ij} =$ Probability of improving the condition state from i to j after a maintenance treatment.

It is important to note that different goals yield different maintenance matrices $\boldsymbol{M}$. For example, if the maintenance goal is SN 20, there are fewer sections to be treated compared to the case where the goal is SN 40 for the same network. In the first case, most of the m_{ij} will be zeros (fewer sections will experience the performance jump), while in the second case, most of the values below the diagonal are greater than zero. Therefore, the maintenance matrix not only depends on the treatment but also on the condition states defined in the model and the maintenance goal. The estimation of the future condition of the network, given a maintenance goal, can be estimated using Equation 18 (Panthi, 2009).

$$\widehat{\boldsymbol{u}_k} = \boldsymbol{u_0} * (\boldsymbol{M} * \boldsymbol{P})^k \tag{18}$$

where:

$\widehat{\boldsymbol{u}_k}$ = Estimated condition of the network at year k based on the maintenance goal and deterioration model.

$\boldsymbol{u_0}$ = Initial condition vector.

$\boldsymbol{M}$ = Maintenance Transition Probability Matrix.

$\boldsymbol{P}$ = Deterioration Transition Probability Matrix.

k = Year to estimate.

Equation 18 reflects the fact that future conditions depend on the initial condition, the maintenance applied, the deterioration of the system, and the period of time between the initial condition and the year to estimate the condition. In this case, the term $\boldsymbol{M}x\boldsymbol{P}$ means that the treatments are applied within one time step. For this framework, it is assumed that this is true; that is, all the skid treatments are applied within one year. This is not strictly required, and different formulations can be done to Equation 18 for different cases (for example, if the treatments are applied every two years) (Zhang, Augenbroe, & Vidakovic, 2005).

6.3 Select Unit Cost of Skid Resistance Treatments

The objective of this step is to identify the treatments that can improve the skid resistance of the pavement and determine their respective costs. The different treatments provide a feedback to the maintenance matrix $\boldsymbol{M}$ defined in the previous step, and the costs impact the investment required for the maintenance policy selected.

The maintenance treatments can be defined as the "set of activities required to keep a component, system, infrastructure asset, or facility functioning as it was originally designed and constructed to function" (Uddin, Hudson, & Haas, 2013, p. 277). For the purpose of the framework, the maintenance treatments are the set of activities that cause a performance jump in the skid condition. The main two parameters that are considered are the unit cost and life-cycle of the treatments (Uddin, Hudson, & Haas, 2013).

The most common maintenance treatment in the case of Texas is the Seal Coat, which is one type of treatment applied to address wet weather crash locations based on the district's Wet Surface Crash Reduction Program (WSCRP). The following is a list of treatments that are applied in different regions of Texas in order to increase skid resistance and to address other pavement condition needs (Brimley & Carlson, 2012) (Long, Wu, Zhang, & Murphy, 2014):

- Milling to increase macro-texture: a short-term solution to address low SN until a construction project can be let.
- Seal Coat: different aggregate classifications and asphalt binder grades are used.
- Strip seals: seal coat in the wheel paths only to reduce costs associated with replacing pavement markings.
- Thin Overlay – less than 2": varies from Type D small top sized aggregate mixes to Type C Coarse mixes depending on district.
- Structural overlays: Permeable Friction Course (PFC); Stone Matrix Asphalt (SMA); Coarse Matrix High Binder (CMHB); and Thicker Type C mixes with stiffer asphalt grades.
- ACP overlay.

Costs vary considerably among these treatments depending on multiple factors, including climate, type of roadway, and traffic volumes. Furthermore, in general, pavement resurface treatment projects are sometimes combined with safety projects that may include road or culvert widening, safety treatment of culverts, rumble strips, additional stripping, and signalization. Further, mobilization and traffic control, which occur for any project, typically are estimated to be 20 percent of project costs, though this percentage can vary based on project location, traffic volume and total project cost. This makes the estimation of a unit cost of pavement resurface treatments difficult; likewise, small projects, remote projects, rural projects, and projects with low paving quantities can result in higher treatment unit costs. It is worth noting that this study focuses on the Benefit-Cost analysis at the network level. Therefore, network-level average costs should be used to conduct the Benefit-Cost Ratio. These costs should be gathered from transportation agencies' pavement management systems or historical project costs.

Likewise, the expected life of the skid improvement must also be determined as part of this component. Unfortunately, there is limited literature about the expected skid performance over time for different types of pavement resurface treatments. Internationally, there have been instances where High Friction Surface Treatments last from seven to twelve years (Federal Highway Administration, 2014). A period of three to seven years has been used as the skid improvement lifetime due to micro-surfacing and chip seal in a previous analysis (Long, Wu, Zhang, & Murphy, 2014). According to Brimley and Carlson (2012), five years is a conservative value of the service life of skid resistance improvements. Due to the limited information about the service life of pavement resurfacing treatments, it is assumed in this framework that treated sections exhibit the same rate of deterioration estimated for untreated pavement; that is, the skid values of treated pavement sections deteriorates at the same rate estimated for the network. Further research is required in this area. Meanwhile, an advantage of this assumption is that it holds the properties of the time-homogenous MC.

6.4 ESTIMATE POLICY COST

The objective of this step is to estimate the cost for the condition-responsive maintenance policy. The process is divided in two steps: 1) the maintenance cost is estimated for a specific goal (skid threshold), and 2) the estimation is performed for multiple goals (skid thresholds) in order to obtain multiple costs.

6.4.1 Estimation of Network Treatment Cost for a Specific Goal

The total cost of a maintenance strategy is calculated based on: 1) the unit skid treatment cost, and 2) the percentage of the network being treated to achieve the skid goal. The latter provides the link between a maintenance strategy and its estimated cost.

In order to quantify the length of the network being treated it is necessary to identify the cumulative distribution function of the frequencies in each condition state. The cumulative distribution function connects the goal with the expected frequencies for a specific condition state (Equation 19).

$$\widehat{m_{t,\imath}} = L * \widehat{\boldsymbol{u}_{t,\imath}} * CDF_i(g) \tag{19}$$

where:

$\widehat{m_{t,\imath}}$ = Estimated number of lane-miles to be treated at year t of condition state i.

L = Total number of lane-miles in the network.

$\widehat{\boldsymbol{u}_{t,\imath}}$ = Estimated percentage of the network in year t that is in condition state i.

$CDF_i(g)$ = Cumulative percentage of the frequencies for condition state i that are below the goal g.

The cumulative distribution of the frequencies depends on the frequency distribution in each condition state. In the case of Texas, the distribution of skid frequencies is uniform for middle ranges of skid (SN 20s to 60s). For SN below 20 or above 70, the frequency distribution is different and must be analyzed case by case, depending on the network.

Once the lane-miles that required treatment are estimated, the unit cost can be used to estimate the maintenance cost as is presented in Equation 20:

$$NCost_t = MUC * \sum_{i=1}^{r} \widehat{m_{t,i}} \quad (20)$$

where:

$NCost_t$ = Nominal maintenance cost for year t.

MUC = Maintenance Unit Cost.

$\widehat{m_{t,i}}$ = Estimated number of lane-miles to be treated at year t for condition state i.

r = Total number of condition states.

The underlying assumption of Equation 20 is that the maintenance unit cost is independent of the skid condition i; however, this might not be true in some cases. For example, it is likely that pavements with low SN require more expensive treatments that are not related only to skid but also to other pavement problems. Due to limited information regarding the treatments cost at the network level, it is not possible to establish a relationship between the SN and treatment cost. However, if this information becomes available, Equation 20 can be rearranged as it is presented in Equation 21.

$$NCost_t = \sum_{i=1}^{r} (\widehat{m_{t,i}} * MUC_i) \tag{21}$$

where:

$NCost_t$ = Nominal maintenance cost for year t.

MUC_i = Maintenance Unit Cost for a specific condition state i.

$\widehat{m_{t,i}}$ = Estimated number of lane-miles to be treated at year t for condition state i.

r = Total number of condition states.

In order to develop the Benefit-Cost analysis for multiple years, it is necessary to take into account the effect of the discount rate (Transportation Economics Committee of TRB, 2016). Each nominal maintenance cost can be converted for a base year using Equation 22. Once the net present value of all the maintenance costs are estimated, the total maintenance cost for a specific goal is estimated using Equation 23.

$$NPCost_t = NCost_t * (1 + h)^{t-t_0} \tag{22}$$

where:

$NPCost_t$ = Net present value of maintenance cost required for year t.

$NCost_t$ = Nominal maintenance cost for year t.

h = Discount rate.

t_0 = Base year.

$$TMC(g) = \sum_{t=0}^{n-1} NPCost_t \tag{23}$$

where:

$TMC(g)$= Total maintenance costs for a specific maintenance goal g.

$NPCost_t$ = Net present value of maintenance cost required for year t.

$n-1$ = Last year that treatments can be applied to the network in the analysis.

6.4.2 Estimation of Network Treatment Cost for Multiple Maintenance Goals

The compilation of the total maintenance cost for different goals is a function that expresses the relationship between the maintenance goal and the maintenance cost. This function is increasing; that is, when the goal increases, the maintenance cost increases. The minimum possible value is zero, which is equivalent to the Do-Nothing maintenance policy. In contrast, the highest possible value is when all of the network is treated every year, which, in other words, represents the case where the goal is so high that it requires that all of the network be treated every year. The actual shape of the function will depend on the network condition in the base year and the deterioration model obtained.

Chapter 7: Estimate Crash Reduction Benefits

Chapter 7 describes the process for estimating the economic benefit of crash reductions. This chapter begins with the estimation of the expected crashes under current condition in the network (7.1). Next, the condition states are linked to the expected crashes through the Crash Rate Ratio (CRR) of SN (7.2). Subsequently, based on the estimated network condition under maintenance and without maintenance, the expected reduction of crashes is estimated (7.3). Finally, the reduction of crashes are monetarized (7.4). The aforementioned process is summarized in Figure 11.

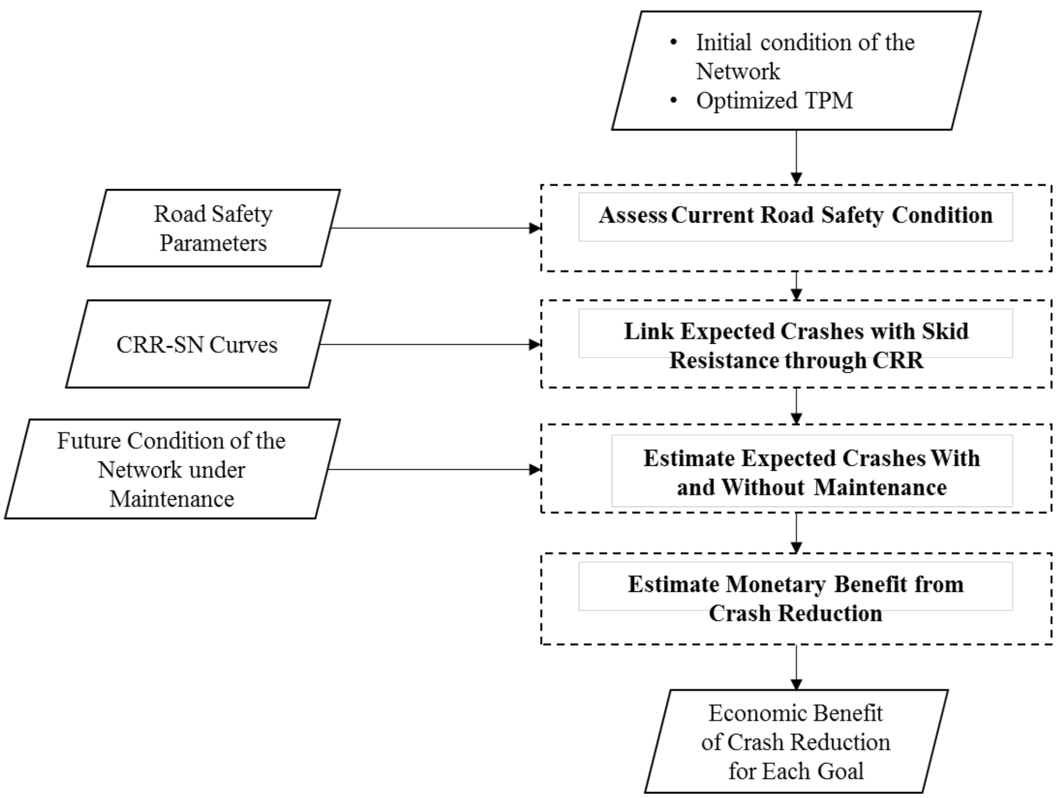


Figure 11: Framework for Estimating Crash Reduction Benefits

7.1 Assess Current Safety Condition in the Network

The objective of this step is to estimate road safety indicators (such as number of crashes or fatalities) in the base year in order to set the initial road safety condition of the model. Because the CRR-SN curves for the case of Texas were developed using number of crashes, the present framework uses the same indicator. The historical number of crashes in the network analyzed can be used to set the initial condition. When this information is not available, the number of crashes can be estimated using Equation 24 (Federal Highway Administration, 2011):

$$C = \frac{R * V * 365 * N * L}{100{,}000{,}000} \tag{24}$$

Where:

C = Total number of crashes expected in the base year.

R = Crash Rate per 100 million VMT.

V = Traffic volumes using Average Annual Daily Traffic (AADT) volumes.

N = Number of years of analysis, which in this case is 1 (only the base year).

L = Total length of the roadway segment in miles.

In the case of the traffic volumes, the value must be consistent to the rest of the analysis. Because the AADT per lane is used to develop the TPMs in this framework, the volume used in Equation 24 is AADT per lane.

7.2 LINK EXPECTED CRASHES WITH SKID RESISTANCE THROUGH CRR

The objective of this step is to link the number of crashes in the network to the skid condition using the CRR-SN curves. The study developed by Long et al. (2014) presents a quantitative relationship between the Crash Rate Ratio (CRR) and the SN. The concept of CRR is based on the cumulated crash counts in a specific network (see subchapter 2.3 Quantification of Impact of Skid Resistance and Crash Risk). Equation 2 presents the relationship between the cumulated percentage of crashes and the cumulated percentage of sections with a SN value below specific values. When this relationship is known in the network (with the calibration of the CRR-SN curves), the cumulated percentage of number of crashes can be estimated. Equation 25 presents the estimated cumulative percentage of crashes as a function of SN.

$$P_{CR}^{SN} = CRR^{SN} * P_{LM}^{SN} \tag{25}$$

Where:

P_{CR}^{SN} = Cumulative percentage of crashes below a specific SN.

CRR^{SN} = Crash Rate Ratio for a specific SN.

P_{LM}^{SN} = The cumulative percentage of total lane-miles at or below a specific SN.

The relationship presented in Equation 25 estimates the value of cumulated crashes for the whole range of SN. However, the condition states for the MC deterioration model aggregates the SN in groups. Therefore, the researcher must approximate the relationship by assigning a CRR value to each condition state. In this framework, a weighted average of the CRR value for each condition state is used. The result is the weighted average of improving a section from one state to another state. In order to diminish the difference due to this approximation, the researcher should disaggregate the states to the maximum extent possible (see subchapter 5.2 Define Skid Condition States). The CRR-SN curves approach one for large values of SN; therefore, the condition states can be aggregated for large values of SN without significantly increasing the differences due to this approximation. In contrast, middle and low values of SN require higher disaggregation of the conditions states in order to capture the CRR differences. Equation 26 presents the estimation of the cumulative percentage of crashes for each condition state.

$$P_{CR}^{i} = CRR_i * P_{LM}^{i} \tag{26}$$

Where:

P_{CR}^{i} = Cumulative percentage of total crashes for condition state i and below.

CRR_i = Crash Rate Ratio associated with condition state i.

P_{LM}^{i} = The cumulative percentage of total lane-miles at or below a condition state i.

It is important to note that the best condition state must have a CRR-SN of one. This restriction represents the fact that 100 percent of the network contains 100 percent of the crashes. However, the definition of the states could lead to a CRR different than one for the best condition (for example, if the best condition state ranges from SN 50 to 100, the weighted average CRR for this condition state will be above one). Therefore, the CRR associated with each condition state needs to be normalized by the value of the CRR associated with the best condition state.

The next step is to find the percentage of crashes in each condition state using the cumulated percentage of crashes. In the case of the lowest condition state, the percentage of crashes is estimated using Equation 26. For the rest of the condition states, the percentage of crashes is estimated using Equation 27. The expected number of crashes for each condition state is estimated using Equation 28.

$$P_c^i = P_{CR}^i - P_{CR}^{i-1} \tag{27}$$

Where:

P_c^i = Percentage of crashes for condition state i.

P_{CR}^i = Cumulative percentage of crashes of condition state i and below.

P_{CR}^{i-1} = Cumulative percentage of crashes of the previous condition state $(i-1)$ and below.

$$C_i = P_c^i * C \tag{28}$$

Where:

C_i = Expected number of crashes in condition state i.

P_c^i = Percentage of crashes for condition state i.

C = Total number of crashes expected in the base year.

Finally, with the expected crashes in each condition state, the researcher can estimate the crash rate per lane-mile for each condition state, as presented in Equation 29 (Federal Highway Administration, 2011). It is assumed that the crash rate per lane-mile is fixed during the study period (four years), which is a realistic assumption because the safety rates do not have dramatic changes within small periods of time (Texas Department of Transportation, 2016).

$$R_i = \frac{C_i}{\boldsymbol{u}_{0,i} * L} \tag{29}$$

Where:

R_i = Crash rate per lane-mile for condition state i.

C_i = Expected number of crashes in condition state i.

$\boldsymbol{u}_{0,i}$ = Percentage of the network with a condition state i in the base year.

L = Total length of the roadway segment in miles.

As a result, there is a quantitative link between the crashes in the network and the skid condition in the network. This information is used in subsequent steps to estimate the crash reduction benefit.

7.3 Estimate Expected Crashes With and Without Maintenance

The objective of this step is to quantify the expected crashes for the Do-Nothing policy and the condition-responsive policy. Once the future condition of the network is known for the two policies (using the deterioration model), the expected number of crashes can be estimated under different scenarios. Equation 30 presents the relationship between crashes in the network and the crash rate per lane-mile for each condition state.

$$C_t = \sum \widehat{\boldsymbol{u}_{t,i}} * L * R_i \tag{30}$$

Where:

C_t = Expected crashes in the network for a specific year t.

$\widehat{\boldsymbol{u}_{t,i}}$ = Estimated percentage of the network with condition state i at year t.

L = Total length of the roadway segment in miles.

R_i = Crash rate per lane-mile for condition state i.

It is important to remember that the CRR-SN quantifies the relationship of crash risk and skid at the network level (Long, Wu, Zhang, & Murphy, 2014). This means that the result of Equation 30 is the overall expected number of crashes at the network level, and not the exact number of crashes, which can be a function of different factors and not only skid (Pratt, et al., 2014).

7.4 ESTIMATE MONETARY BENEFIT FROM CRASH REDUCTION

The objective of this step is to quantify the economic value of the reduction of crashes due to skid improvements. This can be achieved by estimating the weighted average cost per crash. The weighted average cost takes into account the fact that different severities of crashes produce different economic impacts (for example, a property damage crash has less economic impact than a fatality). Equation 31 presents the formula to estimate the unit cost per crash.

$$UCC = \frac{\sum U_s * K_s}{C} \tag{31}$$

where:

UCC = Average unit cost per crash.

U_s = Unit cost of a type of crash severity s.

K_s = Number of people killed or injured by crash severity s, or number of crashes in case of non-injured crash type.

C = Total number of crashes.

The annual benefits can be estimated using Equation 32, using unit cost per crash and the expected crashes per year. It is important to note that the exact number of crashes in the network is a stochastic process that depends on multiple factors. The benefits are based on the expected reduction of crashes but not the actual reduction in the number of crashes.

$$NBenefit_t = UCC * (C_{t,Do-nothing} - C_{t,maintence\ goal}) \tag{32}$$

Where:

$NBenefit_t$ = Nominal benefit of crash reduction for year t.

UCC = Average unit cost per crash.

$C_{t,Do-nothing}$= Expected number of crashes in year t if no treatment is applied.

$C_{t,maintence\ goal}$ = Expected number of crashes in year t if treatments are applied to achieve a specific goal.

In order to develop the Benefit-Cost analysis for multiple years, it is necessary to take into account the effect of the discount rate on the benefits (Transportation Economics Committee of TRB, 2016). Each nominal benefit can be converted for a base year using Equation 33. The sum of the net present value of the benefits is the total benefit for a specific goal, and it is estimated as is presented in Equation 34.

$$NPBenefit_t = NBenefit_t * (1 + h)^{t-t_0} \tag{33}$$

where:

$NPBenefit_t$ = Net present value of economic benefits for year t.

$NBenefit_t$ = Nominal economic benefit for year t.

h = Discount rate.

t_0 = Base year.

$$TB(g) = \sum_{t=1}^{n} NPBenefit_t \tag{34}$$

where:

$TB(g)$= Total economic benefit for a specific maintenance goal g.

$NPBenefit_t$ = Net present value of economic benefits for year t.

n = Total number of years analyzed.

The compilation of the total economic benefit for different goals is a function that expresses the relationship between the maintenance goal and the benefits. This function is increasing: when the goal increases, the number of sections treated increases, while the expected number of crashes in the sections treated decreases. The minimum possible value is zero, which is equivalent to the Do-Nothing maintenance policy (and therefore, no crash reduction nor economic benefit is produced). The highest possible value is achieved when additional skid improvements have negligible reductions in crashes. The actual shape of the function depends on the network condition in the base year, the deterioration model obtained, and the crash rates of the network.

Chapter 8: Benefit-Cost Ratio Analysis

Chapter 8 describes the process for the estimation of the Benefit-Cost Ratio (BCR). This chapter begins with the explanation of the Benefit-Cost Ratio concept (8.1), and continues with the development of scenarios to account for uncertainty (8.2). Figure 12 presents the framework for the estimation of the BCR.

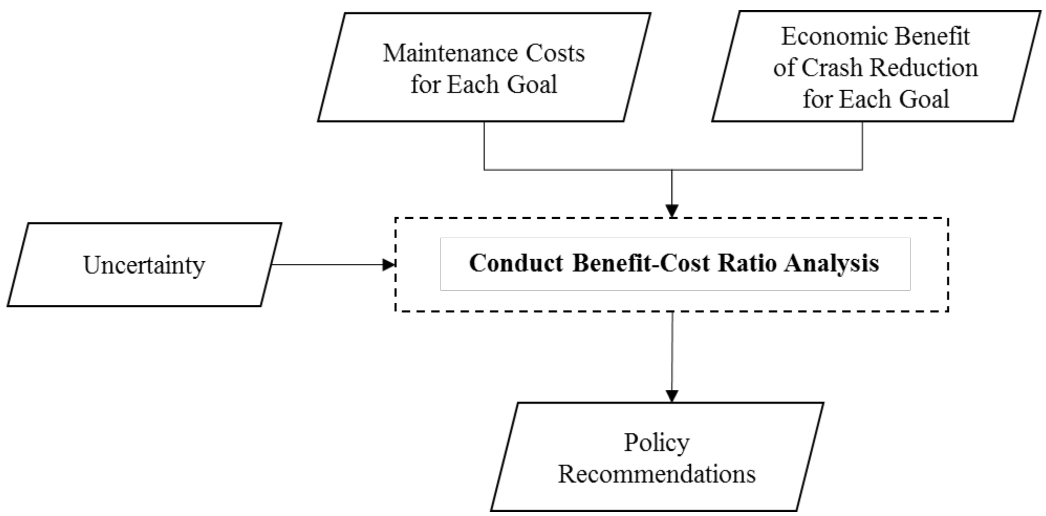


Figure 12: Framework for the Benefit-Cost Ratio Analysis

8.1 ESTIMATION OF BENEFIT-COST RATIO FOR MULTIPLE MAINTENANCE GOALS

The objective of this step is to estimate the Benefit-Cost Ratio (BCR) for multiple goals. As is mentioned in subchapter 2.6 Benefit-Cost Ratio Analyses, the BCR has been used in the last decade to evaluate transportation investments (World Bank, 2010) (Transportation Economics Committee of TRB, 2016). The BCR analysis is recommended when two alternatives are compared; in the case of the present framework, the comparison is between the Do-Nothing maintenance policy and the Condition-

Responsive maintenance policy. The BCR is estimated as the ratio of the benefits and the costs, as is presented in Equation 35.

$$Benefit - Cost\ Ratio\ (BCR) = \frac{Benefit}{Cost} \quad (35)$$

In the case of the present framework, the BCR is not a single value but a vector of multiple ratios for the different maintenance goals (Equation 36). Each maintenance goal will yield a different maintenance cost and a different crash reduction, and by consequence, a different BCR.

$$BCR_g = \frac{TB(g)}{TMC(g)} \quad (36)$$

Where:

BCR_g= Benefit-cost ratio for a specific maintenance goal g.

$TB(g)$= Total economic benefit for a specific maintenance goal g.

$TMC(g)$= Total maintenance costs for a specific maintenance goal g.

The BCR as a function of the maintenance goal is a decreasing function (that is, when the goal increases, the BCR decreases). This is because the reduction of crashes is higher in low skid sections than in middle or high skid sections when a treatment is applied, based on the CRR-SN curves. The actual shape of the function is determined by those parameters defined in the previous chapters; these parameters can be summarized in the deterioration model, treatment costs, the initial skid condition of the network, and the road crashes in the network in the base year.

8.2 DEVELOPMENT OF ONE-VARIABLE SCENARIOS

The objective of this step is to develop scenarios where the impact of variability in the parameters of the model is analyzed. The BCR analysis must include explicitly the uncertainties in the model (World Bank, 2010). One of the ways to do this is to develop one-variable scenarios where the impact of the variability of one parameter is analyzed. The final output is a matrix where, for the different goals, there is a band of low extreme values, average values, and high values of the parameter analyzed (Transportation Economics Committee of TRB, 2016). In the present framework, parameters with uncertainty that can be included in this analysis are:

- Period of time between the assessment and the treatment: that is, if treatments are applied within one time step or not. For example, a pavement section that has a SN below the threshold can be treated within year, or can be treated after two years.
- Maintenance unit cost.
- CRR-SN curve parameters.
- Crash rates.
- Unit cost of crashes.
- Discount rate.

One of the limitations is that the one-variable scenario can be applied only to linear processes. For that reason, the parameters of the MC deterioration model cannot be analyzed with this methodology. Likewise, the AADT cannot be included because it is a potential explanatory variable of the skid deterioration; that is, a different AADT could potentially have a different TPM. In this case, sections in the network with similar AADT can be grouped in order to capture the deterioration process for each group, as is explained in subchapter 4.7 Develop the Transition Probability Matrix For

Heterogeneous Groups. Another limitation is that, at the most, the analysis can only be done to two variables at the same time (Transportation Economics Committee of TRB, 2016).

There are other techniques that can be developed in order to account for uncertainty, such as analytical distributions analysis (if all the variables are linear) or Monte-Carlo Simulation (that can be applied for all variables: linear and non-linear). The advantage of these techniques is that they allow for the analysis of a combination of multiple uncertainties; however, these techniques are out of the scope of the present framework.

Chapter 9: Case Study

This chapter presents the development of the Case Study, using data from the Austin District in Texas. The case study presents an example of each of the modules exposed in the previous chapters.

9.1 DESCRIPTION OF INITIAL SKID DATABASE

Information from the Austin District is used as the case study to build the deterioration model and perform the Benefit-Cost Analysis. The Austin District is located in Central Texas and is composed of 11 counties: Mason, Llano, Gillespie, Burnet, Blanco, Williamson, Travis, Hays, Lee, Bastrop, and Caldwell. The District is responsible for the management of 3,454 center line miles of roads, divided in 8,320 PMIS sections of approximately 0.5 miles (Texas Department of Transportation, 2015). Flexible Pavement is the most common pavement type in the District, which constitutes 95 percent of the center line miles; 46 percent of the center line miles consist of Asphaltic Concrete Pavement (ACP) (Type 5 surface thickness 2.5” – 5.5” and Type 6 surface thickness < 2.5”) and 49 percent consist of Surface Treated pavements (Type 10) which also include pavements with seal coat surfaces. The remaining 5 percent of center line miles is Continuously Reinforced Concrete Pavement (CRCP) (Type 1). The skid database contains data from 2012 to 2015.

9.2 MODEL SKID RESISTANCE DETERIORATION

9.2.1 Define the Skid Resistance Performance Measure

The Austin District collects skid information using the locked-wheel skid trailer, specified by ASTM E274. The test is conducted with a smooth tire at a speed of 50 miles per hour. The SN is estimated using Equation 1 described in subchapter 2.2 Method to Measure Skid.

9.2.2 Define Skid Condition States

The condition states for the case study are defined based on literature and the availability of data. The worse condition state (SN from 1 to SN 20) is defined taking into account that, for the case of Texas, there are instabilities in the CRR-SN curves below a SN of 15 (Long, Wu, Zhang, & Murphy, 2014). In order to avoid these instabilities, this condition state includes the SN up to 20. In addition to this, the Austin District monitors pavement sections that have an SN below 20. For these reasons, the upper bound of the worse condition state is defined as SN 20. The best condition state (SN from 61 to 100) is defined taking into account the minimum data points required to perform the analysis. Values of skid above 70 are infrequent (approximately 4.5 percent of the total data). Thus, if the upper value of SN 74 estimated by Long et al. (2014) is used, it will result in a condition state with few counts and instability in the MC model. By aggregating the SN from 61 to 100 there are enough data points in this condition state to continue the analysis. The condition state with SN from 41 to 60 is defined taking into account that in general, improvements of skid result in increases of SN that are above 40; skid improvements after micro-surfacing generally ranged between low 60s and high 40s (Pratt, et al., 2014) (Federal Highway Administration, 2014). Therefore, this condition state is defined between these two ranges (SN 41 and 60). Finally, the condition states in the middle (SN from 21 to 40) are defined in groups of 5 SN and 10 SN in order to have a more detailed evaluation of the benefits. Table 2 summarizes the six condition states defined for the case study.

Table 2: Condition States Used to Model Skid Resistance

Condition States	Lower Bound	Upper Bound
1	61	100
2	41	60
3	31	40
4	26	30
5	21	25
6	1	20

9.2.3 Estimate Deterioration Probability Matrix

The deterioration model selected for the case study is the Markov Chain process described in Chapter 4: Markov Chain Principles. This model has the advantage of capturing the stochastic behavior of the skid deterioration requiring network level data in order to predict future condition.

9.2.3.1 Select the Data to Model the Deterioration

The following is the criteria used to select the sample to model skid deterioration:

- **Sections with Flexible Pavement:** Only the sections with flexible pavement are considered in the analysis. This is because the Crash Rate Ratio (CRR) curves were estimated only for flexible pavements in Texas (Wu, Zhang, Long, & Murphy, 2014).
- **Historical Data Availability:** Sections with missing values for some of the years 2012-2015 are discarded. It is assumed that the missing data follows the MCAR (Missing Completely at Random) and thus does not affect the sample.
- **Sections without Treatments Applied from 2012 to 2015:** Only the sections without treatments applied during the study period are considered.

For the last criteria, there is no complete information readily available about the sections with or without treatment applied in the study period in the network. Furthermore, there is no quantification in the literature of the SN improvements when pavement treatments are applied. Therefore, it is required to use a criterion to find the sections without treatment. In this case study, the sections with annual increases in SN are considered to have a treatment in the study period. However, not all the increases in SN are due skid improvements, but might be due to uncertainties in the skid measurements. In this framework, the standard deviation of 2 SN, estimated by the ASTM for repeated SN measurements, is used (ASTM International, 2015). A threshold of +6 SN of annual improvement in the SN is selected (that is, three standard deviations above the average or 99% of the cases for a normal distribution). In other words, if a section experiences an annual increase in the SN of 6 or below, it is assumed that is because of the measurement uncertainty around the real value. If a section experiences an annual increase in the SN of 7 or above, it is considered that the section received a pavement resurface treatment, and thus, cannot be used to model the natural deterioration of skid. The sample obtained consists of a total of 1,161 sections, and a length of 564 lane miles.

9.2.3.2 Select the Training and Test Sets

The method used for the selection of the training and test sets is the holdout method (see section 5.3.2 Select the Training and Test Sets), because does not require specialized software. The dataset is randomly subsampled in two groups, one with 70 percent of the data (training set) and the other with the remaining 30 percent (validation set). The TPMs are estimated using Equation 9 with the training set, while the validation set is used to perform the statistical test of the prediction.

9.3.2.3 Develop the Transition Probability Matrix and Prediction of the Future Condition

The sample data covers from year 2012 to 2015; thus, three different annual TPMs can be estimated (TPMs for years 2012-2013, 2013-2014, and 2014-2015). These TPMs are combined in order to have a time-homogenous TPM for the three years as is described in subchapter 5.3.3 Develop Transition Probability Matrix and Predict the Future Condition.

Using Equation 10, the future condition of the network can be estimated using the TPM and the vector of the initial condition. For the case study, the initial condition is the condition in 2012. Table 3 summarizes the number of sections observed and predicted using the TPM, while Table 4 summarizes the relative error of the prediction using Equation 14.

Table 3: Number of Sections Observed (and Predicted) in Each Condition State 2012-2015 for the Training Set with Non-Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2012 (Base Year)	259 (NA)	266 (NA)	125 (NA)	70 (NA)	52 (NA)	59 (NA)
2013	210 (220.4)	247 (253.9)	157 (140.2)	74 (70.7)	65 (69.9)	78 (75.9)
2014	165 (190.9)	257 (237.1)	128 (147.1)	78 (77.6)	96 (83.6)	107 (94.7)
2015	179 (167.4)	205 (218.9)	153 (149.6)	83 (83.9)	97 (96.7)	114 (114.5)

Note: Values in parenthesis are the predicted values using the TPM.

Table 4: Relative Error of Prediction for the Training Set with Non-Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2013	4.9%	2.8%	-10.7%	-4.4%	7.6%	-2.7%
2014	15.7%	-7.7%	14.9%	-0.5%	-12.9%	-11.5%
2015	-6.5%	6.8%	-2.2%	1.1%	-0.4%	0.5%

9.3.2.4 Optimize the Transition Probability Matrix

The TPM matrix is optimized by minimizing the objective function of the square error, which is described in Equation 12. The optimization is performed with the restrictions described in subchapter 5.3.4 Optimize the Transition Probability Matrix, using the generalized reduced gradient nonlinear optimization code incorporated as an add-in to the software Microsoft Excel (Microsoft Excel, 2013). Table 5 presents the TPM after the optimization process, while Table 6 summarizes the number of sections observed and predicted using the optimized TPM. Table 7 presents the relative error of the prediction, where it can be seen that the optimization decreases the relative error as compared to Table 4.

Table 5: Transition Probability Matrix Optimized for the Training Set

Condition States	**1**	**2**	**3**	**4**	**5**	**6**
1	84.8%	2.6%	12.5%	0.0%	0.0%	0.0%
2	0.0%	91.6%	0.0%	4.8%	0.0%	3.7%
3	0.0%	0.0%	85.2%	0.0%	14.8%	0.0%
4	0.0%	0.0%	0.0%	89.3%	10.0%	0.7%
5	0.0%	0.0%	0.0%	0.0%	84.3%	15.7%
6	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

Table 6: Number of Sections Observed (and Predicted) in Each Condition State 2012-2015 for the Training Set with the Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2012 (Base Year)	259 (NA)	266 (NA)	125 (NA)	70 (NA)	52 (NA)	59 (NA)
2013	210 (219.6)	247 (250.4)	157 (139)	74 (75.2)	65 (69.4)	78 (77.5)
2014	165 (186.2)	257 (235)	128 (146)	78 (79.2)	96 (86.6)	107 (98.1)
2015	179 (157.8)	205 (220.1)	153 (147.7)	83 (81.9)	97 (102.6)	114 (120.9)

Note: Values in parenthesis are the predicted values using the optimized TPM.

Table 7: Relative Error of Prediction for the Training Set with Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2013	4.6%	1.4%	-11.5%	1.7%	6.7%	-0.7%
2014	12.8%	-8.6%	14.0%	1.5%	-9.8%	-8.3%
2015	-11.8%	7.4%	-3.5%	-1.3%	5.7%	6.0%

The optimized TPM (Table 5) provides a valuable insight about the skid deterioration in this network. For the condition states 2 and 3, the annual transition due to deterioration is greater than for other condition states, which is represented in the percentages from state 2 to 4, and 3 to 5. This means that the deterioration occurs at a faster rate in these condition states compared to state 1 (the best condition) and condition states 4, 5, and 6 (low conditions). In addition, the TPM is closely approximates a Progressive MC process and not a Sequential MC; for this reason, the Progressive MC is used for the next steps of the analysis.

9.2.4 Perform a Statistical Test of the Prediction

In order to validate the deterioration model, the χ^2 is conducted to evaluate if the difference in the prediction and observed values is significant or not. A value of $\alpha = 0.05$ is used for this test. The null hypothesis is that there are no significant differences between the prediction and the observed values. The test is applied to the training set, and the results are summarized in Table 8. Because the value of p (0.09) is higher than the value of α (0.05), it can be concluded that the differences between the observed and predicted values are not statistically significant; therefore, the optimized TPM can be used to predict the condition of the training set.

Table 8: Results of the Chi-Square Test for the Training Set

Item	**Value**
Degrees of Freedom (m-1) x (n-1)	10
Probability to Reject Null Hypothesis (α)	0.05
Right Tail Critical Value with 10 Degrees of Freedom	18.307
X2 Value	16.205
Probability of the X2 Test (p)	0.09

In order to cross-validate the results of the model, the remaining 30 percent of the data (test set) is used to estimate the deterioration using the same optimized TPM. Next, the result is tested with the χ^2 test. Table 9 summarizes the number of sections observed and predicted using the optimized TPM for the test set, and Table 10 presents the relative error of each of these predictions. Table 11 presents the result of the χ^2 for the test set.

Table 9: Number of Sections Observed (and Predicted) in Each State 2012-2015 for the Test Set with the Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2012 (Base Year)	113 (NA)	91 (NA)	51 (NA)	28 (NA)	20 (NA)	27 (NA)
2013	92 (95.8)	91 (86.3)	51 (57.6)	36 (29.4)	30 (27.2)	30 (33.7)
2014	73 (81.2)	88 (81.5)	59 (61.1)	27 (30.3)	35 (34.4)	48 (41.4)
2015	77 (68.9)	79 (76.8)	53 (62.3)	37 (31)	34 (41.1)	50 (50)

Note: Values in parenthesis are the predicted values using the optimized TPM.

Table 10: Relative Error of Prediction for the Test Set with Optimized TPM

	Condition States					
Year	**1**	**2**	**3**	**4**	**5**	**6**
2013	4.1%	-5.2%	13.0%	-18.5%	-9.3%	12.3%
2014	11.3%	-7.4%	3.6%	12.4%	-1.6%	-13.8%
2015	-10.6%	-2.8%	17.5%	-16.2%	20.9%	0.0%

Table 11: Results of the Chi-Square Test for the Test Set

Item	**Value**
Degrees of Freedom (m-1) x (n-1)	10
Probability to Reject Null Hypothesis (α)	0.05
Right Tail Critical Value with 10 Degrees of Freedom	18.307
X2 Value	11.02
Probability of the X2 Test (p)	0.36

Table 11 shows that the value of p (0.36) is higher than the value of α (0.05), meaning that the differences between the observed and predicted values are not statistically significant. Thus, even with new data, the optimized TPM (Table 5) can be used to predict the future condition of the skid in the network. In subsequent steps, the Case Study applies the framework by taking as the base year the data from 2015, and predicting the condition of the network for 2016, 2017, and 2018.

9.3 ESTIMATE COSTS FOR MAINTAINING SKID RESISTANCE

9.3.1 Define Skid Resistance Maintenance Threshold

In this case study, the maintenance policy selected is the Condition-Responsive policy: a pavement section is treated if, at any given year, it has a SN below a specific SN. It is important to note that the condition-responsive policy is an idealization of skid management; in the real process, a pavement resurface treatment is selected as a combination of multiple factors such as SN, crash history, AADT, and others (see subchapter 6.1 Define Skid Resistance Maintenance). In this case study, the term goal is used as the minimum SN allowed in the network (minimum threshold); in other words, the goal is the minimum SN that a section can have before being treated. The Benefit-Cost analysis is performed for different goals, from a SN of 15 to 100.

9.3.2 Define a Maintenance Transition Probability Matrix for Each Threshold

Once the goals have been defined, it is necessary to associate a Maintenance matrix (***M***) with each goal. For the case study, each matrix M is defined according to the following criteria:

The performance jump of skid is up to condition state 2: This means that the sections treated increase their SN enough to reach state 2 (SN from 41 to 60). Different treatments can be associated with different skid improvement. Public agencies such as the Florida DOT (FDOT) have quantified the Maintenance matrix and the improvements of different parameters after a treatment (Panthi, 2009), but this is not the case for Austin District. However, in general, the new values of skid can be assumed to be to above 40 and below 60 after a treatment (Pratt, et al., 2014) (Federal Highway Administration, 2014).

Number of sections treated in each state is proportional to the goal: Depending on the goal, a different number of sections will need a treatment for each condition state. The number of sections to be treated is a function of the cumulative distribution of sections in each condition state. Condition states 2, 3, 4, and 5 have a uniform distribution of the pavement frequencies. Exceptions are made for condition states 1 and 6, where the cumulative frequency distribution of the number of sections is not uniform. This is shown in Figure 13 and Figure 14.

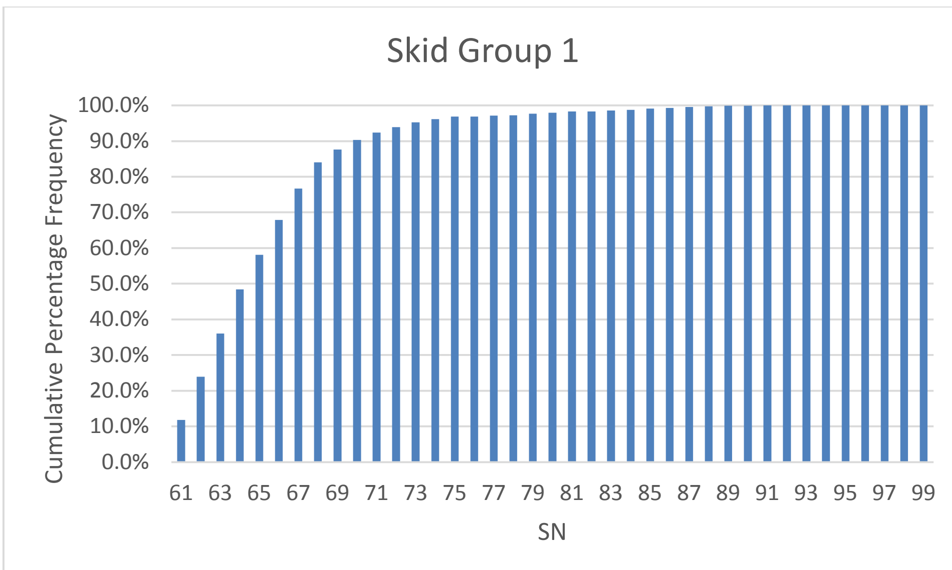


Figure 13: Cumulative Frequency of the Number of Sections for Each Skid Number for State Condition 1

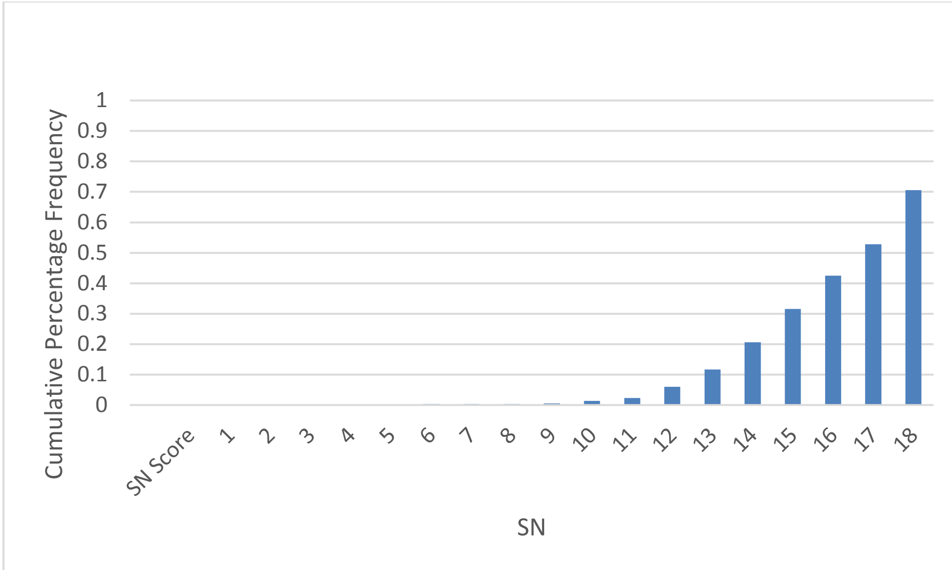


Figure 14: Cumulative Frequency of the Number of Sections for Each Skid Number for State Condition 6

For the condition state 1, almost 90 percent of the data ranges from 60 to 70. Therefore, the frequencies are modeled as two uniform distributions: first, from SN 61 to SN 70 for 90 percent of the frequencies, and the second from SN 71 to SN 100 for the remaining 10 percent of the frequencies. For example, a goal of SN 66 means that 45 percent of the sections of condition state 1 are treated.

For the state 6, almost 100 percent of the data is in the range from SN 12 to 20. Therefore, the frequency distribution for this condition state is modeled as a uniform distribution from SN 12 to SN 20.

All sections are treated within one step (one year): For this case study, all the sections that need treatment are assumed to receive the treatment in the same year.

Once the Maintenance Matrix **M** is defined for each goal, the future condition of the network for each maintenance goal can be obtained using Equation 18.

9.3.3 Select Unit Cost of Skid Resistance Treatments

As explained in subchapter 6.3 Select Unit Cost of Skid Resistance Treatments, different treatments can improve skid such as thin overlay, seal coats, microsurfacing, or chip seals; however, these treatments usually are applied in conjunction with other projects, causing difficulty in quantifying a specific unit cost. The High Friction Surface Treatment (HFST) unit costs are not considered because they are usually applied in small sections of the network (Federal Highway Administration, 2014). In the case of Austin, the most common treatment is the Thin Friction Course Overlay (TFCO).

Specific pavement resurfacing treatments in Texas range from $11,000 to $47,000 per lane mile (Long, Wu, Zhang, & Murphy, 2014) (Broughton & Lee, 2012). In this case study, instead of using the unit cost of one treatment, the preventive maintenance cost from the TxDOT 4-Year Management Plan is used (Liu, Jaipuria, Murphy, & Zhang, 2012). This cost includes the transportation and mobilization of equipment to the treatment location, but does not include any congestion cost associated with the construction work zone.

The cost is indexed to 2014 using the Texas Highway Construction Index (Texas Department of Transportation, 2016b). The updated Preventive Maintenance cost is $42,000 per lane mile. In this paper, a standard deviation (SD) of $5,000 is assumed, and three scenarios are developed: 1) a high cost scenario with a cost 2 SD above the average, 2) an average cost scenario, and 3) a low cost 2 SD below the average. These scenarios are reflected in the BCR analysis.

9.3.4 Estimate Policy Costs

Once the future condition of the network is estimated for each maintenance goal, the number of lane-miles to be treated (Equation 19) and the total maintenance cost per year (Equation 20) can be estimated. Figure 15 presents the results of the maintenance costs for different goals for the three scenarios defined previously: 1) a high cost scenario with a cost 2 SD above the average, 2) an average cost scenario, and 3) a low cost 2 SD below the average. The costs are almost linear from SN 15 to 70 due to the initial condition of the network in 2015, which is almost uniform from SN 20 to SN 70. The number of sections with a SN above 70 is small, and even with a high maintenance goal, there is a slight increase in the cost because there are fewer additional sections to treat.

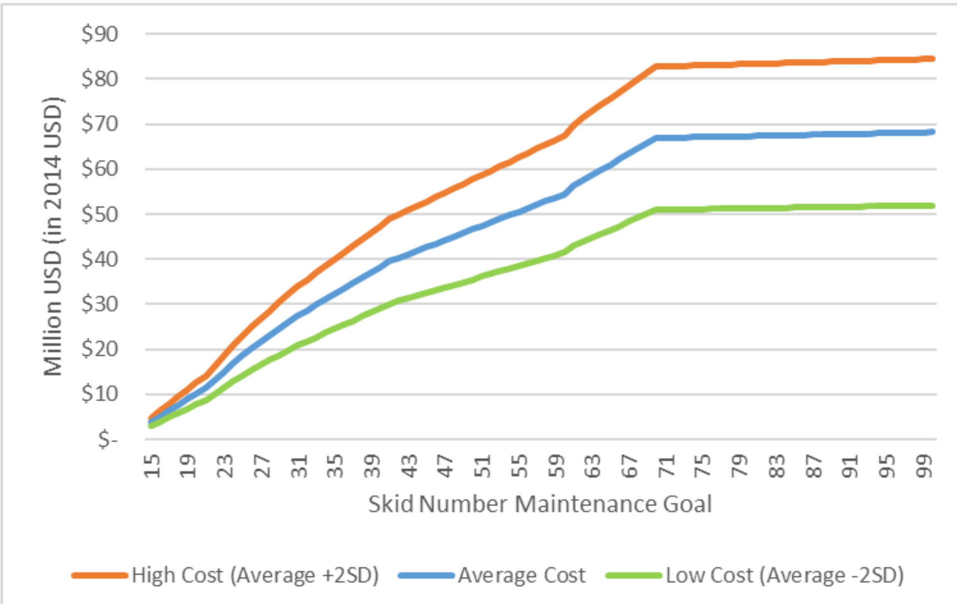


Figure 15: Maintenance Costs for Different Maintenance Goals in the Network

9.4 Estimate Crash Reduction Benefits

9.4.1 Assess Current Road Safety Condition

The number of crashes in the base year (2015) can be estimated using Equation 24. Table 12 summarizes the safety parameters used in the estimation of crashes in this network (Texas Department of Transportation, 2016). The expected number of crashes in the network is 535.

Table 12: Safety Parameters Used to Estimate the Expected Number of Crashes in the Network in the Base Year (2015)

Parameter	**Value**
Annual Crashes per 100 Million Miles Traveled in Texas in 2015	210.3
N	1
Total Mileage	564
AADT per Lane (median)	1,200
Expected Crashes 2015 in the Network	535

9.4.2 Link Expected Crashes with Skid Resistance Through CRR

In this step, the expected number of crashes per lane-mile for each state are estimated using the CRR-SN for Texas. Each condition state will have an associated value of CRR that depends on the SN in their range. The value of the CRR is associated with the middle point of each condition state, except for condition states 1 and 6 where the frequency of SN is not uniform. In these two cases, a weighted average is used to define the "middle point" of condition states 1 and 6.

The study developed by Wu et al. (2014) estimated the CRR curves for all crashes and wet weather crashes in Texas. In this case study, the "all crashes" curves is used for two reasons: first, it is more appropriate to the case study where the expected crashes are not only related to the wet crashes, but also to total crashes. It is important to mention that skid improvements can reduce both wet and dry weather crashes (Hosking, 1986). Second, it is more conservative (the increase of Crash Rate Ratio for low values of SN is lower for the "all crashes" curve than to the "wet crashes"). Equation 37 presents the parameters used in the estimation of the CRR for each condition state.

$$CRR - SN = a * e^{b*SN} + c \tag{37}$$

Where:

a = 3.894

b = -0.04605

c = 0.9205

As it is explained in subchapter 7.2 Link Expected Crashes with Skid Resistance Through CRR, the CRR may need to be normalized to the value of the best condition state. In this case study, since the condition state 1 has its middle point below 72, the CRR associated with this condition state is not 1.0., causing the cumulated percentage of crashes to be above 100 percent. For that reason, the values of CRR are normalized based on the value of CRR of the condition state 1.

Table 13: CRR-SN Associated For Each Condition State

Condition States	Lower Bound	Upper Bound	Middle Point of Condition States	CRR-SN for Each Condition State
6	1	20	16	2.53
5	21	25	23	2.07
4	26	30	28	1.81
3	31	40	36	1.51
2	41	60	51	1.18
1	61	100	67	1.00

Note: In order to obtain a CRR-SN of 1.0 for condition state 1, the values of the CRR-SN for each condition state have been normalized based on the CRR-SN value for condition state 1.

The next step is the estimation of the crash rate per lane-mile, using Equation 25, Equation 27, and Equation 29 as it is presented in subchapter 7.2 Link Expected Crashes with Skid Resistance Through CRR. It is assumed that the crash rates for each condition state are fixed during the period of analysis (four years), which is a realistic assumption because crash rates per mile do not vary dramatically in a four-year period. Table 14 presents the network condition in the base year (2015) of the case study, and Table 15 presents the crash rate estimated for each state.

Table 14: Network Condition in 2015

State	Lane-Miles	Percentage of the Network in Each Condition in 2015	Cumulated Percentage of the Network for Each Condition State
6	79.7	14.1%	14.1%
5	63.6	11.3%	25.4%
4	58.3	10.3%	35.7%
3	100.0	17.7%	53.5%
2	138	24.5%	78.0%
1	124.4	22.0%	100.0%

Table 15: Percentage of Crashes and Crash Rate per Lane-Mile Per Year for Each Condition State

Condition State	Cumulated Percentage of the Network for Each Condition State	Percentage of Crashes Considering Increase of Crash Risk Due to SN	Percentage of Crashes in Each Condition State	Expected Crashes Per Year in Each Condition State	Crash Rate Per Lane - Mile Per Year
6	14.1%	35.8%	35.8%	191.6	2.3
5	25.4%	52.5%	16.7%	89.5	1.4
4	35.7%	64.9%	12.3%	66.0	1.1
3	53.5%	81.0%	16.1%	86.1	0.8
2	78.0%	91.7%	10.8%	57.6	0.4
1	100.0%	100.0%	8.3%	44.4	0.3

9.4.3 Estimate Expected Crashes With and Without Maintenance

Using Equation 30 and the number of lane-miles for each condition state, the expected number of crashes on the network can be estimated. Figure 16 presents the total crash reduction estimated for the network for years 2015-2018.

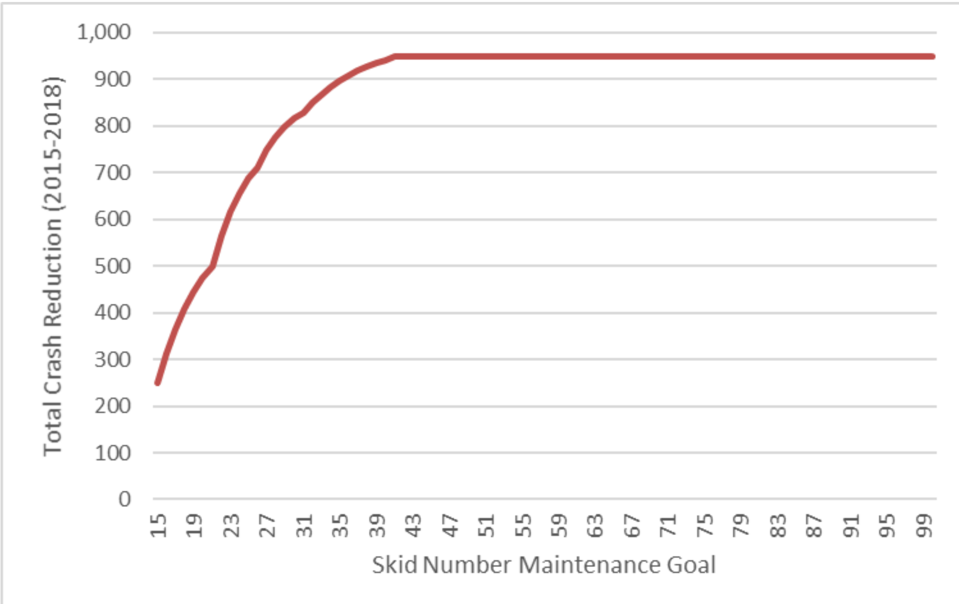


Figure 16: Estimated Crash Reduction in the Network for Years 2015-2018 for Different Maintenance Goals

As Figure 16 shows, there is a higher marginal reduction for lower values of SN goals. When the goal approaches condition state 2 (SN 41-60), the reduction of crashes due to increased skid resistance becomes zero, reflecting the fact that additional treatments will not increase the SN (as was formulated in the creation of the Maintenance Matrix).

9.4.4 Estimate Monetary Benefit from Crash Reduction

The crash information for the Austin District in 2015 is used to estimate the unit cost of a crash. The CRIS database, which contains the crash information for the Austin

District, uses the KABCO scale. The different unit costs are obtained from the National Highway Traffic Safety Administration (2015) updated report in 2015 for the economical and societal costs of crashes.

Table 16: Summary of Crash Data for the Austin District in 2015

Description	Equivalent Letter	Unit Cost (2010 USD)	Count People	Cost (2010 USD)
Killed	K	$9,145,998	276	$2,524,295,448
Incapacitating Injury	A	$1,001,206	1,410	$1,411,700,460
Non-incapacitating Injury	B	$276,010	7,412	$2,045,786,120
Complain of Pain	C	$127,768	9,164	$1,170,865,952
No Injury (Number of Crashes)	O	$42,298	18,849	$797,275,002
Unknown Injury	NA	NA	3,418	NA

Notes: 1) The unit cost for categories A, B, C, and O are obtained from the Appendix D: KABCO Unit Costs of the report *The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised)*, NHTSA, 2015. 2) The unit cost for category K is obtained from the “Table 1-9 Summary of Comprehensive Unit Costs, Reported and Unreported Crashes, 2010 Dollars” in *The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised)*, NHTSA, 2015 3) The O category (No Injury) counts the number of crashes instead of the number of people.

Using Equation 31, the unit cost per crash can be estimated (National Highway Traffic Safety Administration, 2015). According to the NHTSA, the categories K and A are reported always, while for lower severities there are unreported cases. Therefore, the unit cost of the "Unknown Injury" is estimated as the weighted average of categories B, C, and O. Finally, the unit cost per crash is indexed to 2014 USD using the inflation rate of the Bureau of Labor Statistics (2016). The result is a unit cost per crash of $223,000 (in 2014 USD).

9.5 Benefit-Cost Ratio Analysis

The final step is the estimation of the BCR for different maintenance goals. Three scenarios are developed following the different treatment costs established in section 9.3.3 Select Unit Cost of Skid Resistance Treatments: 1) a high cost scenario with a cost 2 SD above the average, 2) an average cost scenario, and 3) a low cost 2 SD below the average. Figure 13 presents the BCR results. The table with the results is in Appendix A.

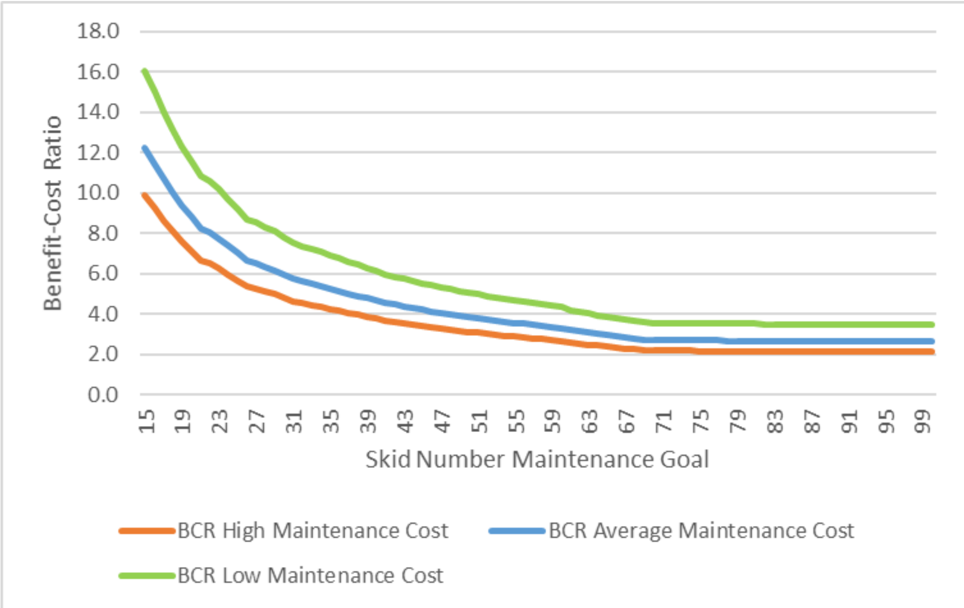


Figure 17: Benefit-Cost Ratio for Different Maintenance Goals

Figure 17 presents some discontinuities around the boundaries of the different condition states defined for the MC. This is due to the association of a CRR for each condition state, meaning that the change in CRR is not continuous from one condition state to the other. In order to have a smoother graph, it is necessary to create more condition states; however, this would require more data in order to model the deterioration properly.

The marginal Benefit-Cost Ratio can also be estimated, but only as a weighted average for each condition state due to the aggregation of the SN in groups. The marginal benefit represents the theoretical BCR of improving one section from condition state *i* to condition state 2. Table 17 and Figure 18 illustrate the marginal BCR trend.

Table 17: Marginal Benefit-Cost Ratio for Each Condition State with Average Maintenance Costs

Condition Group	**Marginal Benefit-Cost Ratio with Average Maintenance Cost**
6 (SN 1-20)	10.8
5 (SN 21-25)	4.8
4 (SN 26-30)	4.3
3 (SN 31-40)	2.5
2 (SN 41-60)	0.0
1 (SN 61-100)	0.0

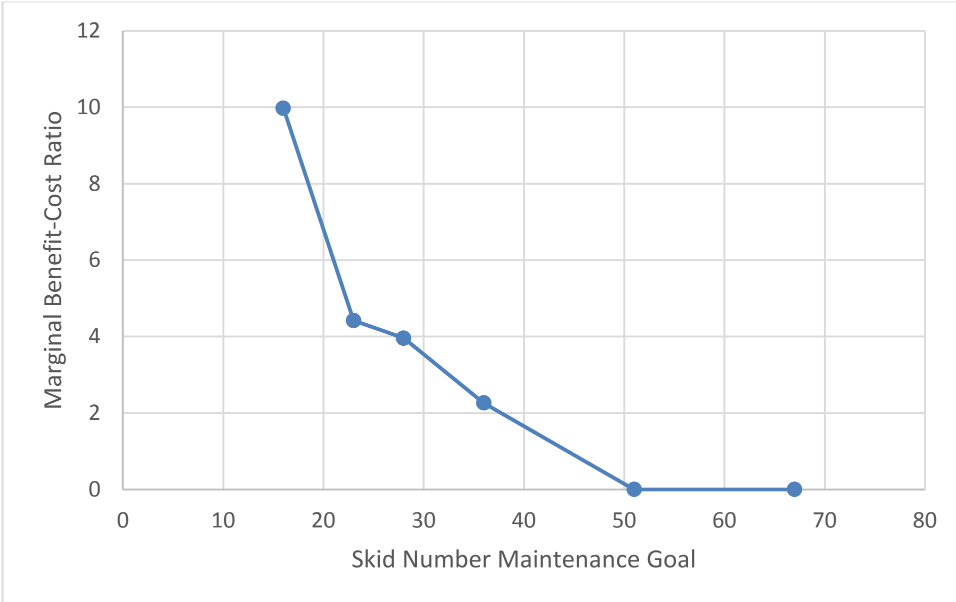


Figure 18: Marginal Benefit-Cost Ratio for Each Condition State with Average Maintenance Costs

9.6 Policy Recommendations

In general, the BCR curves follow the same trends as the CRR-SN curves estimated by Long et al. (2014). This means that, for low values of SN, an improvement has a higher Benefit-Cost Ratio compared to improvements of other condition states. Likewise, it can be observed that the BCR decreases until the maintenance goal reaches the condition state 1 (SN 61-100). This is because, according to the CRR-SN curves, treating sections with SN above 70 will have a negligible reduction in crash risk.

The results show BCR values above 6 for skid thresholds below 30 for the average maintenance cost scenario. Similarly, the BCR for all the analyzed thresholds is above 2.5, even if the threshold is a SN of 60. These results suggest that improving pavement sections with low skid number could yield a positive economic benefit. However, this thesis considered maintenance costs for SN treatments that increase skid up to low 60s. Therefore, the estimation of the BCRs for skid thresholds above 60 must be estimated with the adequate maintenance cost. Finally, the order of magnitudes of the BCRs obtained is comparable with other studies that suggested high BCRs for skid treatments (Federal Highway Administration, 2014; Federal Highway Administration, 2014b) (Long, Wu, Zhang, & Murphy, 2014) (Brimley & Carlson, 2012).

Chapter 10: Summary of Findings and Topics for Future Research

This thesis focuses on the development of a framework to that could assist decision makers in their process of establishing policies for skid maintenance. The current framework can be used to estimate the quantitative benefits of improving skid resistance at the network level. The following are the major findings as a result of the development of the current framework.

10.1 Summary of Research Findings

- There is a proven relationship between the crashes and low skid numbers. Moreover, agencies at the state and national level have identified pavement resurface treatments as cost-effective alternatives to reduce cashes.
- Though there are multiple studies that analyze the relationship between crashes and low skid scores, there are fewer studies that have quantified this relationship. It is in this context that the development of the Crash Rate Ratio (CRR) curves have been proven as a successful way to quantify the relationship between crashes and low skid scores at the network level.
- There is a generalized interest for friction treatments in the last five years, as reported by the Federal Highway (2014). However, analyses of the benefits have been performed in a case-by-case basis. The present framework could provide an alternative to quantify these benefits at the network level.
- The availability of skid data is a challenge. Skid is usually collected, but is not incorporated with other pavement indicators; therefore, the frequency

and coverage of the skid data is limited. This is a challenge for those responsible for managing skid.

- Markov Chain processes can be used to model the deterioration of skid. As is found in the literature and the case study, Markov Chains are able to predict the future condition of the network in a time frame of three to four years.
- Markov Chains are a good alternative for characterizing skid deterioration over other alternatives. Markov Chains have advantages over deterministic models because the Markov Chain model takes into account the stochastic nature of the deterioration process. Likewise, Markov Chains have the advantage of requiring less data than other models (for example, it does not require project level data of the pavement aggregates or long series of time). Markov Chains can be modeled with small time series, and it is not difficult to incorporate new data if required. In a sense, the Markov Chains are in the middle between deterministic models and more complex models that require more data (both for the network and project level). At the same time, the logic and the process of the Markov Chains are easy to explain, which makes the concept easy to share with decision makers and top management.
- Another advantage of the Markov Chains model is the flexibility to adapt to different circumstances. For example, if few data is available for some condition states, the states can be combined and preliminary analyses can be performed until new data is introduced in the model. Likewise, if maintenance policies change, the condition states can be modified and a new analysis can be perform reflecting the policy changes.

- There is a challenge in obtaining quality information for skid treatments. On one side, there is limited knowledge of the quantitative impact of treatments in the skid scores. Likewise, costs are not readily available, especially because few projects address skid only and usually are mixed with others improvements. More research can be done in this aspect.

10.2 LIMITATIONS

The following are the limitations of the current study:

- The current framework is only applicable at the network level. Thus, project level analysis is required when analyzing specific cases. Crashes occur due to a combination of multiple factors, and the increase of skid can cause a reduction of crashes that can be lower or higher than the average value for the network. The BCR estimated should be understood as the expected average benefit at the network level if a given skid threshold is established, and it should not be used as a BCR for a specific project.
- The current framework, which is based on the Markov Chain process, does not take into account explanatory variables within the deterioration model. This is a disadvantage inherited from the Markov chain. Though one of the alternatives to overcome this challenge is the creation of multiple groups of homogenous attributes, this assumes that researchers know beforehand the explanatory variables of skid deterioration. Likewise, it is not possible, in the current framework, to assess the impact of the different explanatory variables on the skid deterioration. If more

skid data becomes available, new models at the network-level can be developed to address this aspect.

- The indicator used in the current framework, the BCR, generally by itself is not a complete metric that indicates the benefits, but it is a complement of other measures. This is a limitation because, in the public sector, the economic benefit is not the only goal to be achieved. In the case of road safety, it can be accompanied by the reduction of crashes and fatalities in the network.
- The current framework does not include congestion costs due to maintenance works. If this information is available, congestions costs can be included in order to have a more precise estimation of the BCR.
- Finally, the applicability or limitation of this framework depends largely on the data available. For example, in the case study, the treatments and costs were limited to those related to preventive maintenance. If more information becomes available related to this aspect, it can be included in the estimation of the BCR. This is not a limitation of the framework itself, but of the availability and quality of the data used as input.

10.3 TOPICS FOR FUTURE RESEARCH

The following are the topics that can be developed in future research:

- If more skid data becomes available, there is the possibility to perform more analysis at the network-level. Topics that can be explored are the quantitative impact of explanatory variables to the skid deterioration process.

- There is a need more for information on pavement resurface treatments. The cost and the quantitative impact of these treatments in the skid score can be explored in more detail in new research. Furthermore, it can be assessed if the skid condition impacts the treatment cost. For example, low skid condition pavements maybe have a higher treatment cost. Likewise, there is a need for more research related to the service life of these treatments.
- Finally, the framework could be expanded to analyze more maintenance policies. The current framework applies the do-nothing and condition-responsive maintenance policy in the analysis.

Appendix A - Results of the BCR Analysis

Table 18. Results of the BCR analysis.

SN Goal	Low Cost (Average -2SD) (Million USD)	Average Cost (Million USD)	High Cost (Average +2SD) (Million USD)	Benefit (Million USD)	BCR Low Cost	BCR Average Cost	BCR High Cost	Reduction of Crashes
15	2.9	3.8	4.8	47.0	16.1	12.2	9.9	206.6
16	3.9	5.1	6.3	58.6	15.0	11.4	9.2	257.6
17	4.9	6.4	7.9	68.5	14.0	10.7	8.6	301.0
18	5.8	7.7	9.5	76.8	13.2	10.0	8.1	337.7
19	6.8	8.9	11.1	83.8	12.3	9.4	7.6	368.5
20	7.8	10.2	12.6	89.7	11.5	8.8	7.1	394.2
21	8.7	11.5	14.2	94.6	10.8	8.3	6.7	415.8
22	10.1	13.3	16.4	106.9	10.6	8.1	6.5	469.8
23	11.5	15.0	18.6	116.6	10.2	7.8	6.3	512.7
24	12.8	16.8	20.8	124.3	9.7	7.4	6.0	546.2
25	14.2	18.6	23.0	130.1	9.2	7.0	5.7	572.0
26	15.5	20.3	25.2	134.6	8.7	6.6	5.3	591.7
27	16.6	21.8	27.0	141.6	8.5	6.5	5.3	622.2
28	17.7	23.2	28.7	147.1	8.3	6.3	5.1	646.4
29	18.7	24.6	30.4	151.4	8.1	6.2	5.0	665.3
30	19.8	26.0	32.2	154.7	7.8	5.9	4.8	679.8
31	20.9	27.4	33.9	157.2	7.5	5.7	4.6	690.8
32	21.8	28.6	35.5	160.9	7.4	5.6	4.5	707.4
33	22.7	29.9	37.0	164.3	7.2	5.5	4.4	722.1
34	23.7	31.1	38.5	167.2	7.1	5.4	4.3	735.1
35	24.6	32.3	40.0	169.8	6.9	5.3	4.2	746.5
36	25.5	33.5	41.4	172.1	6.7	5.1	4.2	756.5
37	26.4	34.7	42.9	174.1	6.6	5.0	4.1	765.2
38	27.4	35.9	44.4	175.8	6.4	4.9	4.0	772.7
39	28.3	37.1	45.9	177.3	6.3	4.8	3.9	779.2
40	29.2	38.3	47.4	178.5	6.1	4.7	3.8	784.8

Table 18, cont.

SN Goal	Low Cost (Average -2SD) (Million USD)	Average Cost (Million USD)	High Cost (Average +2SD) (Million USD)	Benefit (Million USD)	BCR Low Cost	BCR Average Cost	BCR High Cost	Reduction of Crashes
41	30.1	39.5	48.9	179.6	6.0	4.5	3.7	789.6
42	30.7	40.3	49.9	179.6	5.8	4.5	3.6	789.6
43	31.3	41.1	50.9	179.6	5.7	4.4	3.5	789.6
44	31.9	41.9	51.9	179.6	5.6	4.3	3.5	789.6
45	32.5	42.7	52.8	179.6	5.5	4.2	3.4	789.6
46	33.1	43.5	53.8	179.6	5.4	4.1	3.3	789.6
47	33.7	44.3	54.8	179.6	5.3	4.1	3.3	789.6
48	34.3	45.0	55.8	179.6	5.2	4.0	3.2	789.6
49	34.9	45.8	56.7	179.6	5.1	3.9	3.2	789.6
50	35.5	46.6	57.7	179.6	5.1	3.9	3.1	789.6
51	36.1	47.4	58.7	179.6	5.0	3.8	3.1	789.6
52	36.7	48.2	59.7	179.6	4.9	3.7	3.0	789.6
53	37.3	49.0	60.6	179.6	4.8	3.7	3.0	789.6
54	37.9	49.8	61.6	179.6	4.7	3.6	2.9	789.6
55	38.5	50.5	62.6	179.6	4.7	3.6	2.9	789.6
56	39.1	51.3	63.5	179.6	4.6	3.5	2.8	789.6
57	39.7	52.1	64.5	179.6	4.5	3.4	2.8	789.6
58	40.3	52.9	65.5	179.6	4.5	3.4	2.7	789.6
59	40.9	53.7	66.5	179.6	4.4	3.3	2.7	789.6
60	41.5	54.5	67.4	179.6	4.3	3.3	2.7	789.6
61	43.0	56.4	69.9	179.6	4.2	3.2	2.6	789.6
62	43.9	57.6	71.3	179.6	4.1	3.1	2.5	789.6
63	44.8	58.8	72.8	179.6	4.0	3.1	2.5	789.6
64	45.7	59.9	74.2	179.6	3.9	3.0	2.4	789.6
65	46.5	61.1	75.6	179.6	3.9	2.9	2.4	789.6
66	47.4	62.3	77.1	179.6	3.8	2.9	2.3	789.6
67	48.3	63.4	78.5	179.6	3.7	2.8	2.3	789.6
68	49.2	64.6	80.0	179.6	3.6	2.8	2.2	789.6
69	50.1	65.8	81.4	179.6	3.6	2.7	2.2	789.6
70	51.0	66.9	82.9	179.6	3.5	2.7	2.2	789.6
71	51.0	66.9	82.9	179.6	3.5	2.7	2.2	789.6

Table 18, cont.

SN Goal	Low Cost (Average -2SD) (Million USD)	Average Cost (Million USD)	High Cost (Average +2SD) (Million USD)	Benefit (Million USD)	BCR Low Cost	BCR Average Cost	BCR High Cost	Reduction of Crashes
72	51.0	67.0	82.9	179.6	3.5	2.7	2.2	789.6
73	51.0	67.0	83.0	179.6	3.5	2.7	2.2	789.6
74	51.1	67.1	83.0	179.6	3.5	2.7	2.2	789.6
75	51.1	67.1	83.1	179.6	3.5	2.7	2.2	789.6
76	51.2	67.1	83.1	179.6	3.5	2.7	2.2	789.6
77	51.2	67.2	83.2	179.6	3.5	2.7	2.2	789.6
78	51.2	67.2	83.2	179.6	3.5	2.7	2.2	789.6
79	51.3	67.3	83.3	179.6	3.5	2.7	2.2	789.6
80	51.3	67.3	83.4	179.6	3.5	2.7	2.2	789.6
81	51.3	67.4	83.4	179.6	3.5	2.7	2.2	789.6
82	51.4	67.4	83.5	179.6	3.5	2.7	2.2	789.6
83	51.4	67.5	83.5	179.6	3.5	2.7	2.2	789.6
84	51.4	67.5	83.6	179.6	3.5	2.7	2.1	789.6
85	51.5	67.5	83.6	179.6	3.5	2.7	2.1	789.6
86	51.5	67.6	83.7	179.6	3.5	2.7	2.1	789.6
87	51.5	67.6	83.7	179.6	3.5	2.7	2.1	789.6
88	51.6	67.7	83.8	179.6	3.5	2.7	2.1	789.6
89	51.6	67.7	83.9	179.6	3.5	2.7	2.1	789.6
90	51.6	67.8	83.9	179.6	3.5	2.7	2.1	789.6
91	51.7	67.8	84.0	179.6	3.5	2.6	2.1	789.6
92	51.7	67.8	84.0	179.6	3.5	2.6	2.1	789.6
93	51.7	67.9	84.1	179.6	3.5	2.6	2.1	789.6
94	51.8	67.9	84.1	179.6	3.5	2.6	2.1	789.6
95	51.8	68.0	84.2	179.6	3.5	2.6	2.1	789.6
96	51.8	68.0	84.2	179.6	3.5	2.6	2.1	789.6
97	51.9	68.1	84.3	179.6	3.5	2.6	2.1	789.6
98	51.9	68.1	84.3	179.6	3.5	2.6	2.1	789.6
99	51.9	68.2	84.4	179.6	3.5	2.6	2.1	789.6
100	52.0	68.2	84.5	179.6	3.5	2.6	2.1	789.6

Bibliography

ASTM International. (2015). *E274/E274M - 15 Standard Test Method for Skid Resistance of Paved Surfaces Using a Full-Scale Tire.*

Awoke, G. S. (2011). Estimating the Friction Performance of Hot Mix Asphalt Pavements Based On Aggregates Properties And Route Characteristics: Analysis, Modeling and Validation.

Brimley, B., & Carlson, P. (2012). *Using High Friction Surface Treatments to Improve Safety at Horizontal Curves.* College Station, TX: Texas A&M Transportation Institute.

Broughton, B., & Lee, S.-J. (2012). *Microsurfacing In Texas.* Report FHWA/TX-12/0-6668-1. San Marcos: Texas State University.

Bureau of Labor Statistics. (2016). *CPI Inflation Calculator*. Retrieved July 28, 2016, from Databases, Tables & Calculators by Subject: http://www.bls.gov/data/inflation_calculator.htm

Bustos, M., Echaveguren, T., Solminihac, H. d., & Caroca, A. (2006, April). Development of Correlation Equations Between Different Measurements of Skid Resistance in Pavements. *Indian Journal of Engineering & Materials Sciences, 14*, 117-122.

Cavalline, T. L., Whelan, M. J., Tempest, B. Q., Goyal, R., & Ramsey, J. D. (2015). *Determination of Bridge Deterioration Models and Bridge User Costs for the NCDOT Bridge Management System.* Research & Development. Report FHWA/NC/2014-07, NCDOT Project 2014-07. North Carolina DOT.

Choubane, B., Holzschuher, C., & Gokhale, S. (2006). *Precision of Smooth and Ribbed Tire Locked Wheel Testers for Measurement of Roadway Surface Friction Characteristics.* Report FL/DOT/SMO/06-493, State Materials Office. Florida DOT.

Cochran, W. G. (1952, September). The X2 Test of Goodness of Fit. *The Annals of Mathematical Statistics, 23*(3), 315-345. Retrieved from http://www.stat.ucla.edu/~nchristo/statistics100B/goodness_of_fit_test.pdf

Corsello, P. (1993). *Evaluation of Surface Friction Guidelines for Washington State Highways.* Washington State Deparment of Transportation. Report WA-RD 312.1.

Diringer, K., & Barros, R. (1990). Predicting the Skid Resistance of Bituminous Pavements Through Accelerated Laboratory Testing of Aggregates. (W. Meyer, & J. Reichert, Eds.) *Surface Characteristics for Roadways*(1031), 61-76. doi:10.1520/STP23353S

Echaveguren, T., de Solminihac, H., & Chamorro, A. (2010). Long-term Behavior Model of Skid Resistance for Asphalt Roadway Surfaces. *Canadian Journal of Civil Engineering, 37*(5), 719-727.

Federal Highway Administration. (2011, June 28). *Roadway Departure Safety: A Manual for Local Rural Road Owners*. (U. D. Transportation, Editor) Retrieved July 26, 2016, from Appendix C: Crash Rate Calculations: http://safety.fhwa.dot.gov/local_rural/training/fhwasa1109/app_c.cfm

Federal Highway Administration. (2014). *High Friction Surface Treatments Frequently Asked Questions.* Washington D.C.: U.S. Department of Transporation . Retrieved from https://www.fhwa.dot.gov/innovation/everydaycounts/edc-2/pdfs/fhwa-cai-14-019_faqs_hfst_mar2014_508.pdf

Federal Highway Administration. (2014b, October 15). *State Practices to Reduce Wet Weather Skidding Crashes*. Retrieved from Safety: http://safety.fhwa.dot.gov/speedmgt/ref_mats/fhwasa1121/toc.cfm

Fulop, I., Bogardi, I., Gulyas, A., & Csicsely-Tarpay, M. (2000). Use of Friction and Texture in Pavement Performance Modeling. *Journal of Transportation Engineering, 126*(3), 243-248.

Grinstead, C. M., & Sell, J. L. (2012). *Introduction to Probability* (2nd ed.). American Mathematical Society.

Henry, J. J., & Wambold, J. C. (1992). Use of Smooth-Treated Test Tire in Evaluating Skid Resistance. *Transporation Research Record*(1348), 35-42.

Hosking, J. R. (1986). *Relationship Between Skidding Resistance and Accident Frequency: Estimates Based on Seasonal Variation.* Transport and Road Research Laboratory, UK.

Jackson, M. (2008). *Harmonization of Texture and Skid-Resistance Measurements.* University of North Florida. Florida Department of Transportation Research Report http://safety.fhwa.dot.gov/speedmgt/ref_mats/fhwasa1121/sec4.cfm#sec43.

Kallen, M. (2007). Markov Processes for Maintenance Optimization of Civil Infrastructure in the Netherlands. *Ph.D. Thesis*. Delft University of Technology.

Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *International Joint Conference on Artificial Intelligence (IJCAI).* IJCAI. Retrieved from http://ai.stanford.edu/~ronnyk/accEst.pdf

Kuttesch, J. S. (2004). *Quantifying the Relationship Between Skid Resistance and Wet Accidents for Virginia Data.* Blacksburg, VA: Virginia Polytechnic Institute and State University.

Lane, D. M., Scott, D., Hebl, M., Guerra, R., Osherson, D., & Zimmer, H. (2016, November 13). Introduction to Statistics. Online Edition. Retrieved from http://onlinestatbook.com/2/index.html

Liu, W., Jaipuria, S., Murphy, M., & Zhang, Z. (2012). *A Four-Year Pavement Management Plan (FY 2011- FY 2014).* TxDOT Project 5-9035-01. Austin: Center for Transportation Research.

Long, K., Wu, H., Zhang, Z., & Murphy, M. (2014). *Quantitative Relationship between Crash Risk and Pavement Skid Resistance.* Report FHWA/TX-13/0-6713-1. Austin, TX: Center for Transportation Research.

McCullough, B. F., & Hankins, K. (1966). Skid Resistance Guidelines For Surface Iprovements On Texas Highways. *Highway Research Record*, 204-216. Retrieved from https://trid.trb.org/view.aspx?id=104805

McDonald, M. P., Crowley, L. G., & Turochy, R. E. (2006). *Study of Long-Term Pavement Performance (LTPP): Pavement Deflections. Paper 3: Investigation of Seasonal Variation in Pavement Friction Using the Datapave 3.0 Database.* Federal Highway Administration. Washington, D.C.: FHWA Research and Technology. Retrieved from https://www.fhwa.dot.gov/publications/research/infrastructure/pavements/ltpp/06109/paper3.cfm

Microsoft Excel. (2013). *Version 15.0.4859.1000*. (Part of Microsoft Office Professional Plus 2013)

Milton, J. C., Shankar, V. N., & Mannering, F. L. (2008, January). Highway accident severities and the mixed logit model: An exploratory empirical analysis. *Accidents Analysis & Prevention, 40*(1), 260-266. Retrieved from http://dx.doi.org/10.1016/j.aap.2007.06.006

National Highway Traffic Safety Administration. (2015). *The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised).* US Department of Transportation.

National Highway Traffic Safety Administration. (2016). *Traffic Safety Facts.* Report DOT HS 812 013. Washington D.C.: U.S. Department of Transportation. Retrieved from https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812318

Ortiz-Garcia, J., Costello, S., & Snaith, M. (2005). Derivation of Transition Probability Matrices for Pavement Deterioration Modeling. *ASCE Journal of Transportation Engineering, 132*(2), 141-161.

Panthi, K. (2009, November 12). *A Methodological Framework for Modeling Pavement Maintenance Costs for Projects with Performance-based Contracts.* Retrieved from FIU Electronic Theses and Dissertations: http://digitalcommons.fiu.edu/cgi/viewcontent.cgi?article=1163&context=etd

Pardillo, J. M., & Pina, R. J. (2009, July). An assessment of the skid resistance effect on traffic safety under wet-pavement conditions. *Accident Analysis & Prevention, 41*(4), 881-886. Retrieved from http://dx.doi.org/10.1016/j.aap.2009.05.004

PIARC. (2007). *Road Accident Investigation Guidelines For Road Engineers.* World Road Association.

Pratt, M., Geedipally, S., Pike, A., Carlson, P., Celoza, A., & Lord, D. (2014). *Evaluating the Need for Surface Treatments to Reduce Crash Frequency on Horizontal Curves.* Report SWUTC/14/0-6714-1. College Station: Texas A&M Transportation Institute.

Raghunathan, T. (2015). *Missing Data Analysis in Practice.* Chapman and Hall/CRC.

Rai, P. (2011, September 22). *Model Selection and Feature Selection.* Retrieved from Utah State - CS5350/6350 Machine Learning: https://www.cs.utah.edu/~piyush/teaching/22-9-print.pdf

Rezaei, A., & Masad, E. (2013). Experimental-based Model for Predicting the Skid Resistance of Asphalt Pavements. *International Journal of Pavement Engineering, 14*(1), 24-35.
Serfozo, R. (2009). *Basics of Applied Stochastic Processes.* Berlin: Springer-Verlag GmbH.
Smith, A. B., Knighton, J. T., & Guthrie, W. S. (2016). A Statistical Analysis of Network-Level Skid Numbers for Asphalt Pavement Surfaces in Utah. *Transportation Research Board Annual Meeting.* Washington D.C.: Transportation Research Records.
Texas Department of Transportation. (2006). *Wet Weather Accident Reduction Program.*
Texas Department of Transportation. (2008). *Skid System Operator's Manual.* Construction Division, Materials & PAvement Section (CST-M&P).
Texas Department of Transportation. (2015, August 31). *Austin District Statistics*. Retrieved November 27, 2016, from http://www.txdot.gov/inside-txdot/division/finance/discos.html?dist=AUS
Texas Department of Transportation. (2016). *Comparison of Motor Vehicle Traffic Deaths, Vehicle Miles, Death Rates, And Economic Loss 2003-2015.* Austin, TX.
Texas Department of Transportation. (2016b). *Highway Cost Index (1997 Base) Index Report for July 2016.* Construction Division - Contract Letting.
Transportation Economics Committee of TRB. (2016). *Transportation Benefit-Cost Analysis*. Retrieved November 14, 2016, from Transportation Economics: http://bca.transportationeconomics.org/
Uddin, W., Hudson, W. R., & Haas, R. (2013). *Public Infrastructure Asset Management.* McGraw-Hill Education.
Weiss, N. A. (2008). *Introductory Statistics* (Eighth ed.). Boston, MA: Pearson Education, Inc.
World Bank. (2010). *Cost-Benefit Analysis in World Bank projects.* Washington, D.C.: The World Bank Group. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/2561/624700PUB0Cost00Box0361484B0PUBLIC0.pdf?sequence=1
World Health Organization. (2016). *Decade for Action of Road Safety 2011-2020.* Retrieved from United Nations Road Safety Collaboration: http://www.who.int/roadsafety/decade_of_action/en/
Wu, H., Zhang, Z., Long, K., & Murphy, M. (2014). Considering Safety Impacts of Skid Resistance in Decision-Making Processes for Pavement Management. *Transportation Research Record: Journal of the Transportation Research Board*(2455), 19-27.
Yang, J. (2004). Road Crack Condition Performance Modeling Using Recurrent Markov Chains and Artifictial Neural Networks. *Graduate Thesses and Dissertations*. University of South Florida. Retrieved from Scholar Commons: http://scholarcommons.usf.edu/etd/1310
Zhang, Y., Augenbroe, G., & Vidakovic, B. (2005). Uncertainty Analysis in Using Markov Chain Model to Predict Roof Life Cycle Performance. *10DBMC*

International Conference On Durability of Building Materials and Components. Lyon.

Zimmer, R., & Fernando, E. (2013). *Evaluation of Skid Measurements Used by TxDOT: Technical Report.* Report FHWA/TX-13/0-6619-1. College Station, TX: Texas A&M Transportation Institute.

Vita

Oscar Galvis was born in Bogota, Colombia. After completing his work at Claretiano High School, Bogota, in 2006, he entered the University of Los Andes in Bogota, Colombia. He received an award and scholarship due to his high scores in the national high school test. He received the degree of Bachelor of Science in Civil Engineering in August 2011. During the following three years, he was employed at CDM Smith working on freight planning and road safety projects. He received the Core Values Excellence award while working there. In January 2011, he entered the Graduate School at the University of Texas at Austin.

Address: oscargalvis@utexas.edu

This manuscript was typed by Oscar Daniel Galvis Arce.