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DEVELOPING A FRAMEWORK TO QUANTIFY THE BENEFIT COST RATIO OF SKID RESISTANCE INTERVENTION THRESHOLDS AT THE NETWORK LEVEL

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DEVELOPING A FRAMEWORK TO QUANTIFY BENEFIT COST RATIO OF SKID RESISTANCE INTERVENTION THRESHOLDS AT THE NETWORK LEVEL

by

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Dedication

I dedicate this work to all the people affected by the 2021 winter storm. People with plans, dreams, and projects like all of us but that are not with us now. You will be remembered.

Acknowledgements

I want to thank God, through whom all things are possible, and who provides us with everything we need.

I want to thank my family, for all the support given. This achievement is not only mine, but it is my wife's and family's achievement as well.

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Finally, I want to thank everyone that invested time and supported us. This is your achievement as well.

God may bless you all.

Abstract

Developing A Framework To Quantify The Benefit Cost Ratio Of Skid Resistance Intervention Thresholds At the Network Level

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Research has proven that low values of pavement friction increase crash rates. For this reason, highway agencies such as the Federal Highway Administration (FHWA) and the American Association of Highway and Transportation Officials (AASHTO) have provided guidelines for the management of pavement friction, including minimum friction levels recommended for roadway networks. Following these recommendations, some state transportation agencies have established minimum friction thresholds in terms of the Skid Number (SN). Additionally, FHWA lists the Benefit-Cost Ratio (BCR) as one of the methodologies that can assist decision makers in the definition of these thresholds. However, there are limited studies conducted to quantify the BCR when determining the minimum SN threshold for a roadway network. The objective of this study is to fill this research gap by providing a methodology to quantify the BCR when establishing minimum pavement friction thresholds for roadway networks. The first step is to develop models for characterizing the deterioration of skid resistance and predict its future conditions for two scenarios: 1) base scenario where no treatments are applied, and 2) improvement scenario

where treatments are applied. Benefits are estimated in terms of the monetary value of crash reductions. Costs are estimated by considering: a) the cost of applying treatments to pavement sections, b) the monetary value of travel time delays associated with work zones, and c) the monetary value of road safety risks associated with work zones. A case study was first developed to assess the accuracy of Markov Chain processes to model skid resistance deterioration. Then, the proposed methodological framework for BCR estimation was applied to a roadway network consisting of 993 highway sections in Texas as a case study to demonstrate its applicability. The case study analysis was performed for three groups of roadways: Interstate Highways, Urban Freeways, and Arterials and Collectors. The research findings indicate that the proposed methodology can provide transportation agencies with an analytical tool to effectively estimate the BCR of maintenance policies intended to establish a minimum SN for a roadway network. Moreover, an analysis was conducted to examine the impact of three alternatives that incorporate SN into the Pavement Management Plan (PMP). The results suggest that there are potential benefits of incorporating SN-related targets into the overall pavement management process.

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Chapter 1: Introduction

Road crashes are considered a public health concern worldwide. Just in the U.S. alone, over 35,000 people were killed in traffic accidents and over 3 million were injured during 2016 (NHTSA, 2019). For this reason, transportation agencies at the national, state and local levels continuously improve their programs to provide safer infrastructure to road users, including monitoring minimum friction levels for a roadway network.

1.1 Standard Tests to Measure Pavement Friction

Crashes are the consequence of multiple interdependent factors that generally can be grouped into those related to the driver, the vehicle, the environment and highway condition. Within the highway condition there are multiple factors that transportation agencies can control such as geometric design, roadside clearance, or pavement surface conditions. Pavement friction is one of the factors within the pavement surface conditions that affect crash rates.

According to AASHTO, pavement friction can be summarized as the "force that resists the relative motion between a vehicle tire and a pavement surface" (AASHTO, 2008, p. 15). Pavement friction is a complex process that involves pavement micro-texture, pavement macro-texture, tire design, environmental conditions such as water films on the pavement, and the relative speed between the pavement and the tire (AASHTO, 2008). In some cases, site-specific friction conditions are measured for high-crash locations. However, at the network level, transportation agencies generally measure pavement friction by using standardized indirect measurements.

There are two common measures used to monitor pavement friction: The Sideways Force Coefficient (SFC) and the Skid Number (SN). The SFC is generally used globally, especially in European countries and countries of the Commonwealth. In the U.S., most of the transportation agencies measure friction and collect friction data in terms of the Skid Number (also called Friction Number (FN) in some states). The SN is an indirect standard measure of pavement friction that is described by the ASTM E274/E274M – 15 (ASTM International, 2015). During this test, a truck with a locked-wheel skid trailer is drive at a constant speed. This skid trailer has a vertical weight W that is known. Water is sprayed in front of tire to produce a water film thickness (Figure 1 and Figure 2). 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.

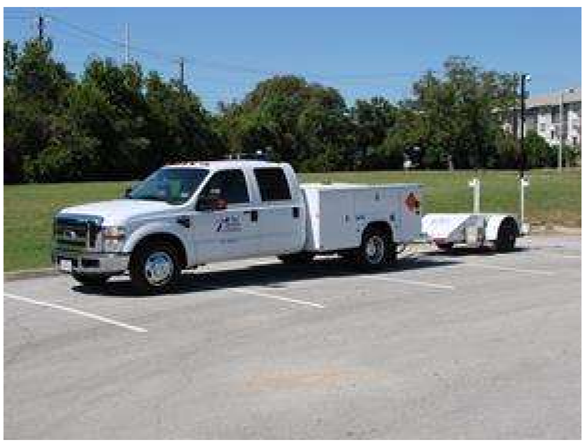


Figure 1: Skid Truck and Trailer Used by TxDOT (TxDOT, 2019)

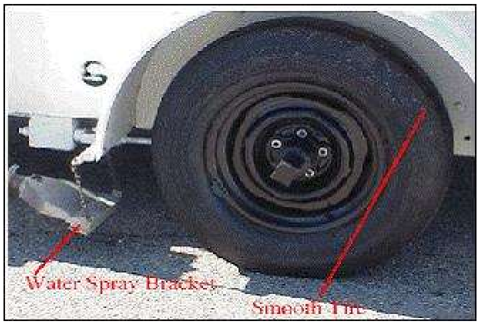


Figure 2: Detail of Skid Trailer (TxDOT, 2019)

The tractive force F between the tire and the pavement surface is recorded during this test. Then 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 the speed V of the trailer and the type of tire T.

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

T = Indication of the tire used in this test, ribbed (R) or smooth (S)

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

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

1.2 Relationship Between Friction Level and Crashes

Multiple researchers have concluded that low values of pavement friction (in terms of either SFC or SN) increase crash rates. McCullough and Hankins (1966) analyzed 517 rural sections on Texas Highways and recommended a minimum level of pavement friction for Texas roads. Rizenbergs et al (1976) analyzed wet-weather crash rates on rural highways in Kentucky, and concluded that crash rates increase at a higher rate below a SN70 (Skid Number measured at 70 miles per hour) of 27 (Figure 3). Kuttesch (2004) indicated that the risk of wet weather crashes increases as the SN decreases, based on a dataset from the Virginia Wet Accident Reduction Program. Viner et al. (2004) reviewed the skid resistance policy of the United Kingdom and concluded that low SFC values increase the mean crash rates of highways segments with no junctions and no curves (Figure 4). Cenek and Davies (2004) analyzed SCRIM® data from New Zealand's State Highways and estimated that increasing the SFC by 0.1 yields a crash rate reduction of 20 percent for all crashes and 35 percent for wet crashes. The authors also found that skid resistance improvements have a higher role decreasing crash rates than texture improvements. Pardillo and Jurado (2009) analyzed data from two-lane rural roads in Spain and concluded that improving the SFC from a mean value below 50 to a value of 60 reduces wet-pavement accidents by 68 percent on average, with a higher reduction being observed on curve sections. Pratt et al. (2014) concluded that SN is a relevant factor in the estimation of run-off-road crashes on horizontal curves. Wu et al. (2014) quantitatively linked crash rates with the SN condition of the Texas Highway network, and concluded that crash rates increase exponentially when pavement sections are below SN 28 (Figure 5). Geedipally et al. (2017) concluded that the SN is a statistically significant factor in the estimation of a Crash Modification Factor (CMF) for horizontal curves. Alhasan et al. (2018) analyzed the impact of SN on roadway departure crashes for the highway network in Iowa. The study correlated crash data from 2006 to 2016 with pavement condition attributes, and concluded that pavement sections with high values of SN have significantly lower crash rates for both dry and wet conditions. In summary, a wide range of available literature concludes that low values of SN increase crash rates.

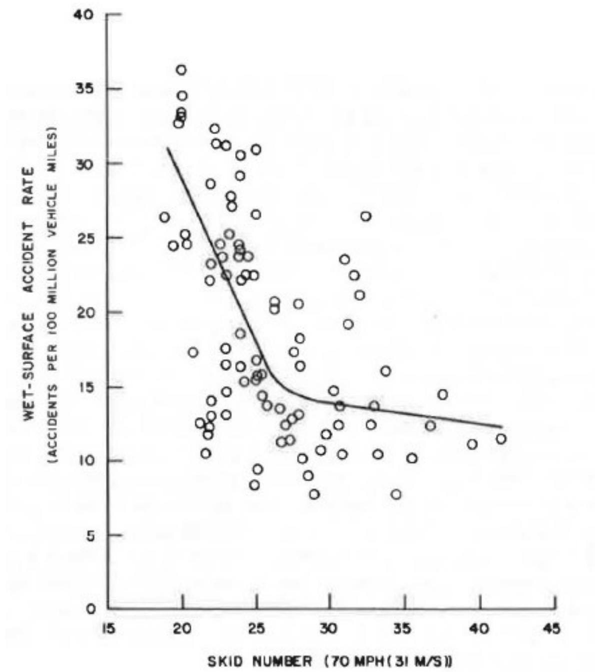
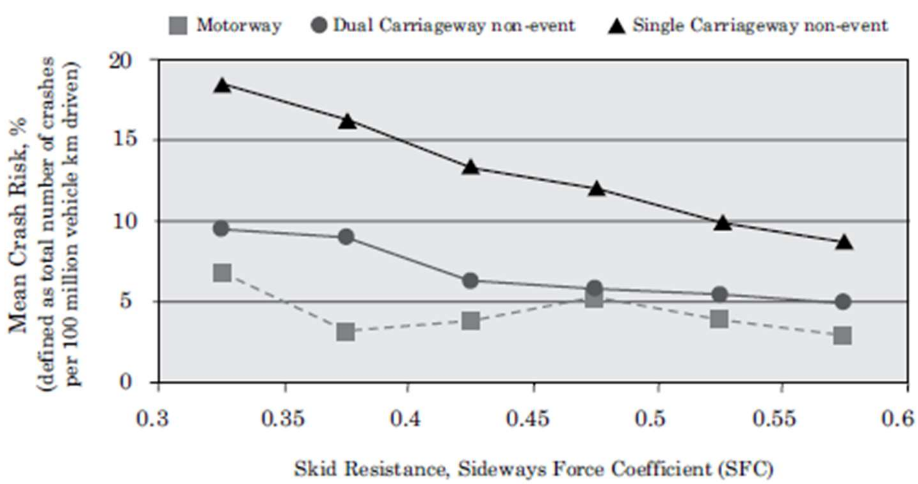


Figure 3: Wet-Surface Crash Rates as a Function of Skid Number Measured at 70 Miles Per Hour (Rizenbergs, Burchett, Deacon, & Napier, 1976)



NOTES: Dual Carriageway = 4-lane divided highway; Single Carriageway = undivided highway; Non-event = segments with no junctions, crossings or notable bends or gradients.

Figure 4: Mean Crash Risks for Roadway Networks in the United Kingdom (Viner, Sinhal, & Parry, 2004)

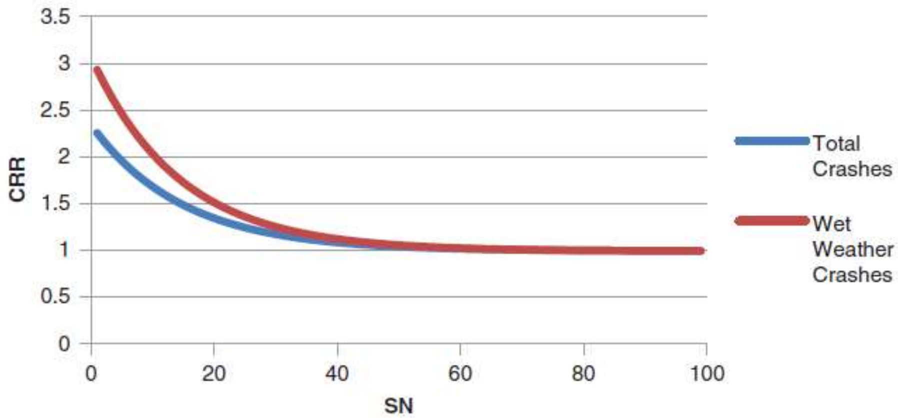


Figure 5: Crash Rate Ratio as a Function of Skid Number (Wu, Zhang, Long, & Murphy, 2014)

1.3 Investigatory and Intervention Thresholds

Highway agencies usually manage their pavements at two levels: project level and network level (Haas, Hudson, & Zaniewski, 1994). At the project level, agencies focus on defining the best Maintenance and Rehabilitation (M&R) strategy for a given project. Therefore, at the project level the analysis is site-specific and the results obtained from actions performed have application to other locations up to a certain extent. In contrast, at the network level the focus are the policies and budget planning for the whole network, thus comprising a group of pavement sections. For skid resistance management at the network level, the primary objective is to establish investigatory thresholds and intervention thresholds for a roadway network. These thresholds have been defined for the whole network as guidelines for further investigation or actions, with a reduced focus on specific conditions of the highway sections.

The FHWA issued a Technical Advisory providing guidance to transportation agencies for the management of pavement friction. The most recent version, which was updated in 2010 under T 5040.38 “Pavement Friction Management,” highlights the importance of collecting pavement friction data at the network level and identifying high-risk sites for further investigation or intervention (FHWA, 2010). Similarly, AASHTO recommends establishing investigatory and intervention thresholds in order to identify sites with low pavement friction (AASHTO, 2008). The investigatory threshold is the threshold at which a project-level evaluation of the site should be performed to assess if an intervention is needed. The intervention threshold is the friction value that triggers the treatment of a pavement section when the friction of the section is below the intervention threshold. According to FHWA (2010), the establishment of both thresholds should be based on a safety analysis of friction needs, but it may also include the analysis of "costs and benefits of providing specific friction levels." In other words, an economic analysis could provide additional guidance to transportation agencies in the definition of these thresholds.

Following the guidelines of AASHTO, some transportation agencies have established investigatory and intervention thresholds that fit their particular conditions. In general, transportation agencies collect the SN data for the whole network, then analyze the data with other crash information such as collision history, field investigation, and roadway geometrics in order to assess if an action is required. For instance, in Florida, when the FN40R (Friction Number measured at 40 mph with a Ribbed tire) is lower than 28 (for posted speeds less than 45 mph) or 30 (for posted speeds greater than 45 mph), project-level investigation is conducted to determine if remedy actions are needed if the section is not programmed for resurfacing (FHWA, 2014). In New York, the New York State Department of Transportation (NYSDOT) identifies locations with a high proportion of wet weather crashes. Subsequently, skid resistance is measured in all these locations and the NYSDOT performs the following actions based on the skid resistance values obtained: a) if the FN40R is below 32, project-level investigation is conducted; b) if the FN40R is below 26, immediate action is performed (FHWA, 2014). In Texas, some districts of the Texas Department of Transportation (TxDOT) perform a treatment action if the SN50S (Skid Number measured at 50 mph with a Smooth tire) is below 20 (Wu, Zhang, Long, & Murphy, 2014). Wu et al. (2014), based on crash rates estimations for the state of Texas, proposed three thresholds: Minimum SN (SN50S = 14), Vigilant SN (SN50S = 28), and Desirable SN (SN50S = 72) (for the rest of the document, SN will refer to Skid Number measured at 50 mph with a Smooth tire). When the skid resistance of a pavement section falls below the Minimum SN, intervention was recommended. Between the Vigilant and Minimum SN, project-level testing was recommended. Between the Desirable and Vigilant SN, continued network-level vigilance was recommended. Finally, the Desirable SN (and above) were considered to be the SN values where skid resistance improvements would yield little reduction in crash rates.

1.4 Previous Benefit-Cost Ratio Studies

Although some DOTs have established investigatory and intervention thresholds, there are few studies conducted to estimate the Benefit-Cost Ratio (BCR) when establishing these thresholds for a network. Most of the literature have focused on case-by-case estimations; therefore, the results were applicable at the project level but not at the network level. For example, South Carolina DOT estimated the before-and-after BCR of High Friction Surface Treatments (HFST) installation on curved sections, obtaining values ranging between 1 and 24 (FHWA, 2014b). Similarly, the Kentucky Transportation Cabinet estimated the before-and-after BCR of HFST installation on 26 curves, obtaining values ranging between 1.9 and 6.2 (FHWA, 2014b). Wilson et al. (2016) estimated the BCR over 5-years of HFST installation on 17 tight curves (curves with a radius less than

1,000 feet) in Florida. The BCR ranged between 0 and 118, with an average BCR of 24.5 for total crashes.

In contrast, there are few studies that estimate the BCR of establishing investigatory or intervention thresholds at the network level. Moreover, the available studies did not develop a methodology for such estimations that would allow a transportation agency to replicate the analysis because either the treatment cost or the benefit of crash reduction were typically based on engineer's judgement, assumptions or local experience. For example, Cook et al. (2011) estimated the BCR of New Zealand's skid resistance policy and obtained values ranging between 13 and 35. However, the results are approximate as the crash reductions were obtained by comparing two different highway groups (one group where the policy was applied and another group where the policy was not fully applied) instead of directly linking crash rates to skid resistance condition. Brimley and Carlson (2012) estimated the BCR of HFST installation on horizontal curves in Texas rural roads, and obtained a BCR ranging between 20 and 60 over a 5-year time horizon. However, these estimations were preliminary as well given that the benefits were estimated assuming hypothetical crash reductions instead of an actual quantitative relationship between crashes and the SN condition. The service life of the treatments was also assumed in this study. Long et al. (2014) performed a preliminary estimation of the BCR, over a 4-year period, of improving SN=14, SN=28, and SN=74 to SN=75. The resulting BCRs were 39.6, 20.0, and 0.99, respectively. The study was preliminary because the cost part was an approximation due to of lack of information.

1.5 Objective of This Study

Based on the background information presented in the previous sections, it can be seen that, following AASHTO's Guide for Pavement Friction recommendation, some

DOTs have established investigatory and intervention thresholds as a way to manage pavement friction. Moreover, a benefit-cost analysis could provide additional guidance to transportation agencies in the definition of these thresholds; especially from the perspective of its cost-effectiveness. However, there is limited literature regarding benefit-cost analyses of establishing investigatory and intervention thresholds at the network level. Previous studies are approximations based on engineer's judgement, assumptions or local experience. Additionally, previous studies did not develop a methodology that would allow an agency to replicate the analysis process. The primary objective of this study is to fill this research gap by providing a methodology to estimate the BCR of establishing an intervention threshold for pavement friction at the network level.

1.6 Proposed Methodological Framework

In order to accomplish the objective, the study will focus on the methodology to estimate of the BCR when an intervention threshold for SN is established for a network. This maintenance strategy consists in treating pavement sections with SN values below or equal to the intervention threshold, which is the strategy that some DOTs have already adopted. Discussions assessing if the intervention threshold strategy is the best maintenance strategy for managing skid resistance will be out of the scope of this study.

The methodological framework comprises three components: (a) the development of a skid resistance deterioration model, (b) the estimation of the costs due to skid resistance treatments, and (c) the monetary value of crash reductions and other indirect costs resulted from skid resistance improvement. The generic framework is depicted in Figure 6.

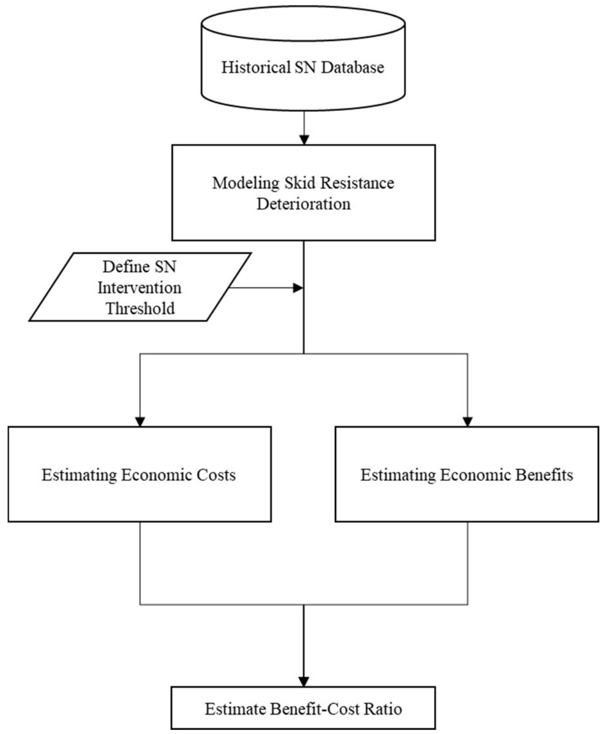


Figure 6: Generic Framework for the Estimation of the Benefit-Cost Ratio of Establishing a Friction Intervention Threshold at the Network Level

1.7 ORGANIZATION OF THE DISSERTATION

The research for this dissertation was divided in three phases. The first phase focused on developing a deterioration model (first box of Figure 6). This first phase is explained in Chapter 2. The second part focused on the estimation of the Benefits and Costs associated with establishing the SN minimum threshold and it is explained in Chapter 3. Finally, Chapter 4 analyzes three alternatives to incorporate SN into the pavement management process.

Chapter 2: Modeling Skid Resistance Deterioration At the Network Level Using Markov Chains

As mentioned in Chapter 1, the first step to estimate the Benefit-Cost Ratio of establishing a SN intervention threshold is to model skid resistance deterioration. The deterioration model is used to estimate future condition of SN in the network for the base scenario (when no treatments are not applied) and the intervention threshold scenario (when treatments are applied). The objective of this study was to test the feasibility of using a Markov Chains model for pavement skid deterioration at the network level to predict future SN condition.

This chapter contains extracts from a manuscript that has been published and is available in INTERNTATIONAL JOURNAL OF PAVEMENT ENGINEERING, February 18th, 2019, http://tandfonline.com/10.1080/10298436.2019.1578882[1]

2.1 Background

Traffic accidents are usually a result of multiple factors, where low pavement friction can be one of these contributing factors. The theory of skid-related crashes can be explained as a supply-demand problem: the supply of friction is provided by the road-tire interaction, while the demand of friction is a function of the driving characteristics such as speed (Pratt, et al., 2014). It has been observed that the risk of crashes increases when the difference between supply and demand of friction decreases (Wu, Zhang, Long, & Murphy, 2014).

[1] Galvis Arce, O. D., & Zhang, Z. (2019). Skid Resistance Deterioration Model At the Network Level Using Markov Chains. *International Journal of Pavement Engineering*. doi: 10.1080/10298436.2019.1578882
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Because of the impact of pavement skid resistance on crash risk, some state and local agencies in the U.S. started to manage pavement skid resistance in their networks as part of the pavement management process. It is important to recognize that highway agencies typically manage their pavements at two levels: project level and network level (Haas, Hudson, & Zaniewski, 1994). At the project level, attention is given to determining the best Maintenance and Rehabilitation (M&R) action for a specific section using more detailed information. At the network level, the focus is on using the percentage of pavement sections in each condition category for budget planning and M&R plan development. In particular, at the network level, minimum skid resistance thresholds have been established to ensure that a minimum level of SN be provided to road users for their safety. Consequently, to ensure that the minimum level of pavement skid resistance be met during the development of a pavement maintenance and rehabilitation (M&R) program over a planning horizon, models for pavement skid resistance deterioration should be developed.

Based on existing literature, available skid resistance deterioration models can be grouped in two categories (Echaveguren, Solminihac, & Chamorro, 2010; Rezai & Masad, 2013): 1) physical models where variables affecting the condition deterioration of a pavement, such as aggregate types and traffic characteristics, are used as the primary explanatory variable, and 2) time series models where time is the main explanatory variable. For physical models, skid resistance deterioration is modeled as an initial skid value that drops until it reaches a final, constant skid resistance value. This final skid resistance value is usually a function of aggregate properties and, sometimes, is combined with other variables such as climate conditions (Echaveguren, Solminihac, & Chamorro, 2010). Physical models have been used mostly for analysis at the project level where more detailed section-specific information is available. In general, the advantage of the physical models is that they offer a physical explanation of the pavement skid resistance deterioration; however, these models require more data collection efforts compared with the time series where pavement skid resistance deterioration is modeled as a function of time. Time series models have been used mostly for analysis at the network level. Time series models are easier to calibrate and require less data compared with physical models. Because the present study focuses on a network-level analysis, the literature review focused on time series models.

Ahammed and Tighe (2014) analyzed the long-term behavior of skid resistance for both asphalt pavements and Portland cement pavements using data extracted from the Long-Term Pavement Performance (LTPP) database. The researchers were able to model skid resistance deterioration as a function of million vehicle passes. Li et al. (2017) performed a survival analysis of friction deterioration for flexible pavements. The researchers analyzed data from the Interstate Highway in Pennsylvania and were able to estimate the probability of keeping friction values above a defined threshold. Fulop et al. (2000) developed a Markov Chain (MC) model to predict the future friction condition at the network level for Hungarian asphalt highways, where a sample of the network was used to estimate the pavement friction deterioration from one year to another. The model successfully characterized the deterioration of the pavement friction for a four-year time period.

After analyzing the different models available in the literature, two criteria are used to select the model to characterize SN deterioration: 1) the input required to develop the model, and 2) the feasibility of using the output for developing a Maintenance and Rehabilitation (M&R) budget plan and programming at the network level. After the comparison of the different models, it was found that the most suitable model to characterize SN deterioration is a Markov Chain (MC) process. The MC process is selected because the data requirements for estimating MC models are more consistent with the data availability for most transportation agencies, especially for characterizing skid condition at the network level. More specifically, it is common that pavement aggregate properties are not available for every pavement section of an entire pavement network, thus hindering the development of physical models. In contrast, MC process can be used to model the skid resistance deterioration process using historical SN data that is commonly available for highway agencies in the U.S. In other words, the MC model would allow highway agencies to have a quantitative model for estimating M&R needs in terms of SN requirements even if aggregate properties are not available to them.

The literature is scarce on skid resistance deterioration models at the network level using an MC process. This lack of MC models to characterize pavement skid deterioration contrasts with the broad use of this modeling tool in other infrastructure deterioration processes such as pavements, bridges and pipes deterioration (Jiang, Saito, & Sinha, 1989; Yang, 2004; Kallen, 2007; Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). Moreover, MC models have been explored by various studies to predict the pavement condition deterioration such as PSI, PCI, or even IRI for up to 5-6 years (Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). Therefore, the objective of this study is to apply the MC modeling process to characterize pavement skid resistance deterioration at the network level.

This chapter is organized as follows. A definition of the MC process is summarized. Then, the methodological framework for the MC estimation is presented. To demonstrate the applicability of the method, a case study is conducted by applying the modeling process to a sample of pavement sections in the Austin District of the Texas Department of Transportation (TxDOT). Finally, the results and conclusions of this study are presented.

2.2 Mathematical Definition of the Finite-Space, Time-Discrete and Time-Homogenous MC Process

The MC has four main components: space, transition probabilities, and time step. The space is a set of finite conditions states defined as: $S = \{s_1, s_2, \dots, s_r\}$ where r is the total number of condition states. A transition probability is defined as the probability of jumping from one state s_i to s_j in one-time step, and it is denoted as p_{ij}. The time is represented as an ordered discrete set $\tau = \{t_0, t_1, \dots, t_n\}$ where $t_0 < t_1 < \cdots < t_n$. The time-homogenous MC is a special case of MC where the transition probabilities p_{ij} are constant for all the set τ.

Let i and j represent two condition states of S. The transition probability between condition states i and j in a time-homogenous MC can be described as:

$$p_{ij} = \Pr\{X_{k+1} = j \mid X_k = i\} = \Pr\{X_1 = j \mid X_0 = i\} \tag{2}$$

Where:

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

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

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

The MC processes have the property that the future condition of the system depends only on the current condition and is independent of the previous conditions. Transitions among condition states can be arranged in a matrix called the Transition Probability Matrix (TPM) denoted as $\boldsymbol{P}$. The TPM is square with each entry representing p_{ij}. The number of columns and rows is equal to the total number of condition states r (Equation 3).

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{bmatrix} \tag{3}$$

Because the entries of the TPM are the transition probabilities, each 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 $\sum_{j=1}^{r} p_{ij} = 1$.

Two types of TPM are commonly used to model infrastructure deterioration: progressive TPMs and sequential TPMs. In both processes, the condition transitions from a higher condition state to a lower condition state. However, in sequential TPMs, the condition is forced to transition through all the states before reaching the worse state. The selection of a progressive or sequential TPM in the model will depend on the deterioration rates observed. Equations 4 and 5 present examples of a TPM for a progressive and sequential process, respectively.

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ 0 & p_{22} & p_{23} & p_{24} \\ 0 & 0 & p_{33} & p_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & 1 - p_{11} & 0 & 0 \\ 0 & p_{22} & 1 - p_{22} & 0 \\ 0 & 0 & p_{33} & 1 - p_{33} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

2.3 Methodology

The development of the skid resistance deterioration model is composed of three steps: (a) pre-process Skid Number data, (b) estimate the deterioration TPM, and (c) perform a statistical test of the predicted pavement skid condition for validation purposes. This process is summarized in Figure 7.

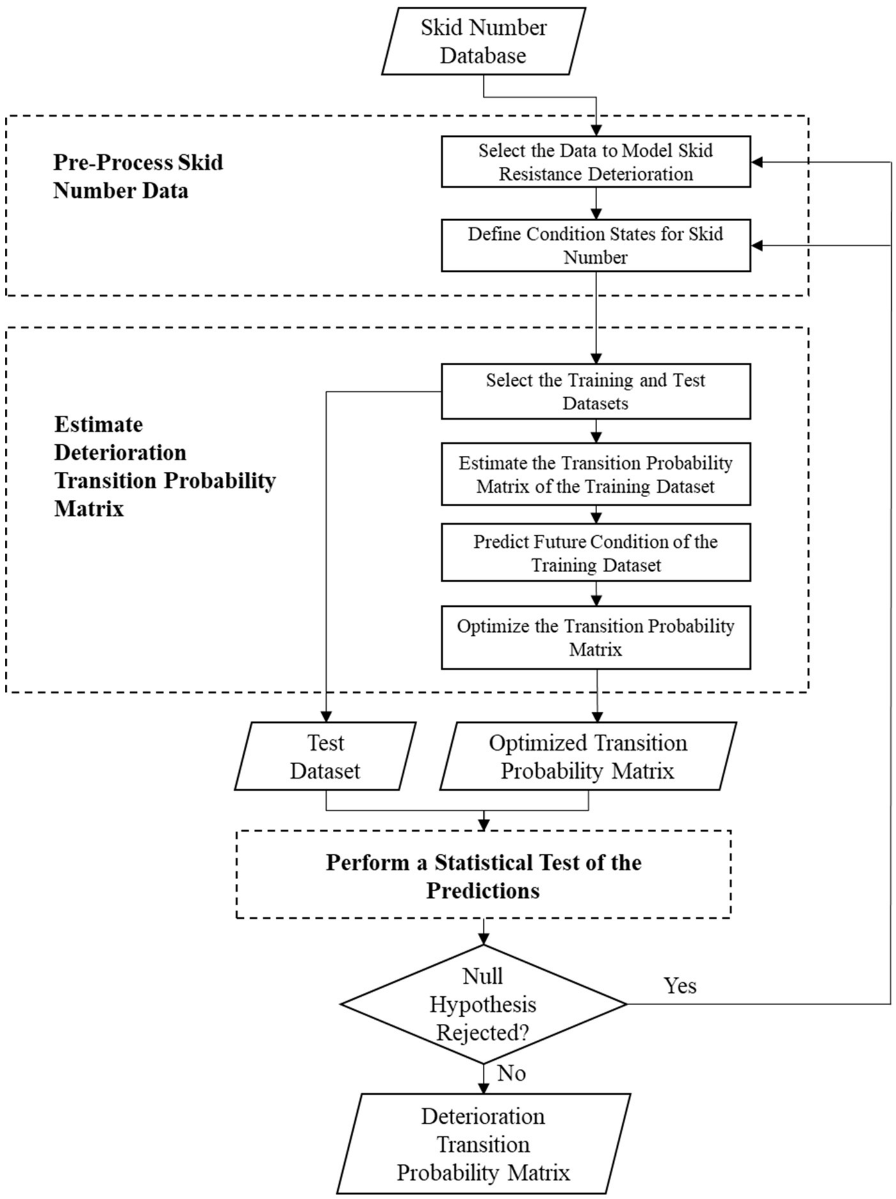

Figure 7: Framework to Develop a Skid Resistance Deterioration Model Using Markov Chains

Pre-Process Skid Number Data

Select the Data to Model Skid Resistance Deterioration

In order to develop the skid resistance deterioration model that represents a natural deterioration process it is necessary to filter out pavement sections that received any improvement treatments during the study period from the database. The filtering process can be performed by filtering out pavement sections that show an increase in SN from one year to another during the study period. However, it is important to mention that SN values have associated measurement errors due to the data collection equipment. In the case of the SN measurements following ASTM E274/E274M – 15, it is estimated that the SN measurement has a standard deviation of 2 around the 'real' value of SN (ASTM International, 2015). Therefore, sections with an annual increase in SN that is within the precision of the test (for example, an annual SN improvement of 2 SN) do not necessarily represent pavement sections with skid resistance improvements. Consequently, these sections can be kept in the dataset for analysis.

Define Condition States for Skid Numbers

There are no strict rules for defining condition states for SN in the literature. However, based on MC models developed for other infrastructure deterioration (Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000; Kallen, 2007; Panthi, 2009), the following recommendations were followed:

1. Condition states must be ordered from the best condition state to the worst condition state. For this study, the condition states represent the different ranges of SN values for the pavement skid resistance. 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.

2. Condition states can be defined using SN thresholds already defined by a highway agency if such thresholds exist.
3. Ranges of the condition states must guarantee a minimum of five pavement section observations every year. This restriction is necessary because the statistical test applied to validate the model (the Chi-Square test) requires a minimum of at least five observations for each condition state.

It is worth noting that the selection of the number of condition states is a trade-off between the representativeness of the deterioration process and the SN data available. A high number of condition states would provide a deterioration model that could be more detailed, but at the same time would require more data collection efforts. In contrast, a small number of condition states requires less data, but its use could be limited in terms of its effectiveness in performing predictions. In general, infrastructure deterioration has been modeled with four to ten condition states (Butt, Shahin, Feighan, & Carpenter, 1987; Jiang, Saito, & Sinha, 1989; Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000; Kallen, 2007; Panthi, 2009; Abaza, 2015; Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015) with the final number of condition states depending on the data availability and the objective of the study.

Estimate Deterioration Transition Probability Matrix

Estimating the deterioration TMP consists of four steps. First, the dataset is divided in two exclusive subsets: a training dataset, which is selected to estimate the pavement skid deterioration TPM; and a test dataset, which is selected to validate the TPM obtained with the training dataset. In this study, the two datasets are selected using the Holdout procedure, which consists of randomly dividing the dataset into two subsets of 2/3 (training dataset) and 1/3 (test dataset) proportions (Kohavi, 1995).

Second, the TPM of the time-homogenous MC is estimated using the ‘counting proportions’ formula. This formula is based on the observed SN values during a study period, as is presented in Equation 6 (Panthi, 2009).

$$\hat{p}_{ij} = \frac{\sum_{t=1}^{n} N_{t,ij}}{\sum_{t=1}^{n} \sum_{j=0}^{r} N_{t,ij}} \tag{6}$$

Where:

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

$\sum_{t=1}^{n} N_{t,ij}$ = Number of observed transitions from state i to state j during the study period.

$\sum_{t=1}^{n} \sum_{j=0}^{r} N_{t,ij}$ = Total number of observed transitions from state i to all other states during the study period.

n = Total number of years observed.

r = Total number of condition states in the model.

Third, the skid resistance condition for the training dataset is estimated for the years following the base year. This estimation is conducted in order to calibrate the model by reducing the error between the predicted values and the observed values. Equation 7 presents the condition estimation of the network at year t as a function of the initial condition at year 0 and the TPM.

$$\widehat{\boldsymbol{u}_t} = \boldsymbol{u}_0 \boldsymbol{P}^t \tag{7}$$

Where:

$\widehat{\boldsymbol{u}_t}$ = Estimated condition vector (probabilities for each of the condition states) at year t.

$\boldsymbol{u}_0$ = Initial condition vector (probabilities for each of the condition states) at year 0.

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

Finally, the TPM is optimized by minimizing the error between the predicted values and the observed values. This study uses the squared difference as the objective function (Equation 8) (Butt, Shahin, Feighan, & Carpenter, 1987; Jiang, Saito, & Sinha, 1989; Fulop, Bogardi, Gulyas, & Csicsely-Tarpay, 2000; Kallen, 2007; Panthi, 2009; Abaza, 2015; Cavalline, Whelan, Tempest, Goyal, & Ramsey, 2015). The Generalized Reduced Gradient (GRG) Non-linear algorithm, which is included in Microsoft® Excel, was used to minimize the error.

$$Min \sum_{t=1}^{n} \sum_{i=1}^{r} \left(\boldsymbol{u}_{t,i} - \widehat{\boldsymbol{u}}_{t,i}\right)^2 \tag{8}$$

Where:

$\boldsymbol{u}_{t,i}$ = Observed condition state probability i at year t.

$\widehat{\boldsymbol{u}}_{t,i}$ = Estimated condition state probability i at year t.

$n =$ Total number of years observed.

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

It is recommended that the optimization procedure be performed assuming a progressive TPM. This recommendation is important because optimizing a progressive TPM can result in a sequential TPM if the data follows a sequential deterioration trend, but the opposite is not true. After the optimization process, the resulting TPM needs to be reviewed to confirm if the TPM is sequential by checking that virtually the condition transit through all states before reaching the worse state, and that no condition state is skipped. The conditions for the optimization of the progressive TPM are described below:

1. Values in the diagonal of the TPM, except for the lowest condition state, must be in the range of $[0,1)$. This restriction means that $0 \leq p_{ii} < 1$. In the case that $p_{ii} = 0$, it implies that all the pavement sections with SN condition state i deteriorate from this condition to other condition states in one year.
2. The lowest condition state of the TPM is an absorbing state. In other words, $p_{ii} = 1$ when i is the worst SN condition state. This restriction implies that once a pavement section reaches this SN condition state, the SN does not deteriorate further.
3. Values below the diagonal are zero. In other words, $p_{ij} = 0$ for $j < i$. The reason is that each value below the diagonal represents an improvement in the SN condition of the pavement, which should be zero unless a maintenance treatment is applied.
4. Values above the diagonal of the TPM range between $[0,1]$, or $0 \leq p_{ij} \leq 1$ for $j > i$. This restriction represents that the SN of the pavement sections in condition state i can deteriorate from condition state i to lower condition states in one year.
5. The sum of the rows of the TPM are equal to 1. In other words, $\sum_{j=1}^{r} p_{ij} = 1$ where r represents the total number of condition states. This restriction enforces that the

SN condition of a pavement either 1) remains in the same condition, or 2) deteriorates to lower condition states.

Perform a Statistical Test of the Prediction

The last phase of the proposed framework is the validation of the deterioration model using the Chi-Square Goodness-of-Fit Test. The null hypothesis (H_0) is that the predicted condition is not significantly different from the observed condition. The value of α is set to 0.05. The test is conducted twice: first, it is conducted for the training dataset, and then it is conducted for the test dataset. In order to reject H_0, the probability of obtaining the estimated Chi-Square (p) must be less than α (that is, $p < \alpha$). If one of the tests rejects H_0, it would imply that the differences between the observed skid condition of the network and the predicted skid condition of the network are significantly different, thus meaning that the deterioration model failed. Equation 9 presents the formula to estimate the Chi-Square test value for the SN deterioration model.

$$\chi^2 = \sum_{t=1}^{n}\sum_{i=1}^{r}\frac{(\boldsymbol{u}_{t,i} - \widehat{\boldsymbol{u}}_{t,i})^2}{\boldsymbol{u}_{t,i}} \quad (9)$$

Where:

χ^2 = Chi-Square value.

$\boldsymbol{u}_{t,i}$ = Observed condition state probability i at year t.

$\widehat{\boldsymbol{u}}_{t,i}$ = Estimated condition state probability i at year t.

n = Total number of years observed.

r = Total number of condition states in the model.

There are two potential reasons that would cause low accuracy in the prediction model. First, the SN data being modeled can be heterogeneous and one TPM cannot model different skid resistance deterioration rates. To overcome this limitation, SN data can be grouped by pavement characteristics such as similar climate, AADT, similar aggregates of the pavement, or functional class of the road, among others (Thompson, et al., 2012). Second, there is not sufficient data to guarantee a representative estimation of the probabilities for all the condition states. To overcome this limitation, adjustments to the condition states such as merging some conditions or increasing the ranges for some conditions may be needed (Thompson, et al., 2012). These two corrective actions are represented in the loop of Figure 7.

2.4 Numerical Case Study

The dataset used to conduct the case study was obtained from the Austin District of the Texas Department of Transportation (TxDOT). Most of the pavement sections, 94.1 percent to be specific, in the Austin District correspond to flexible pavements, or Asphaltic Concrete Pavement (ACP), while only 5.1 percent are Continuously Reinforced Concrete Pavement (CRCP). The Skid Number data was extracted from the Texas Pavement Management Information System (PMIS) from 2012 to 2015.

Pre-Process Skid Number Data

Select the Data to Model Skid Resistance Deterioration

Three criteria were used to filter the dataset such that the resulting dataset would best represent the natural deterioration of pavement skid resistance. These criteria are:

1. **Sections with Flexible Pavement:** This case study was focused on flexible pavements for the reason that they are the most common pavement type in the Austin District.

2. **Sections without Skid Improvements from 2012 to 2015:** Only pavement sections that received no skid improvements during the study period were included in the dataset in order to model the natural deterioration of pavement skid resistance.
3. **Historical Data Availability:** Sections with missing SN values during the period of 2012-2015 were discarded because these sections could not be effectively used to estimate the TPM.

Based on these filtering rules, the resulting sample dataset had a total of 1,161 sections, representing 14.7 percent of the total number of pavement sections in the Austin District. Figure 8 presents the histogram of the SN distribution of the sample dataset for the base year (2012). As can be seen in this figure, the sample dataset covered a wide range of pavement skid conditions, with approximately 90 percent of the pavement sections falling between SN 20 and 70, and 32.9 percent falling below SN 35.

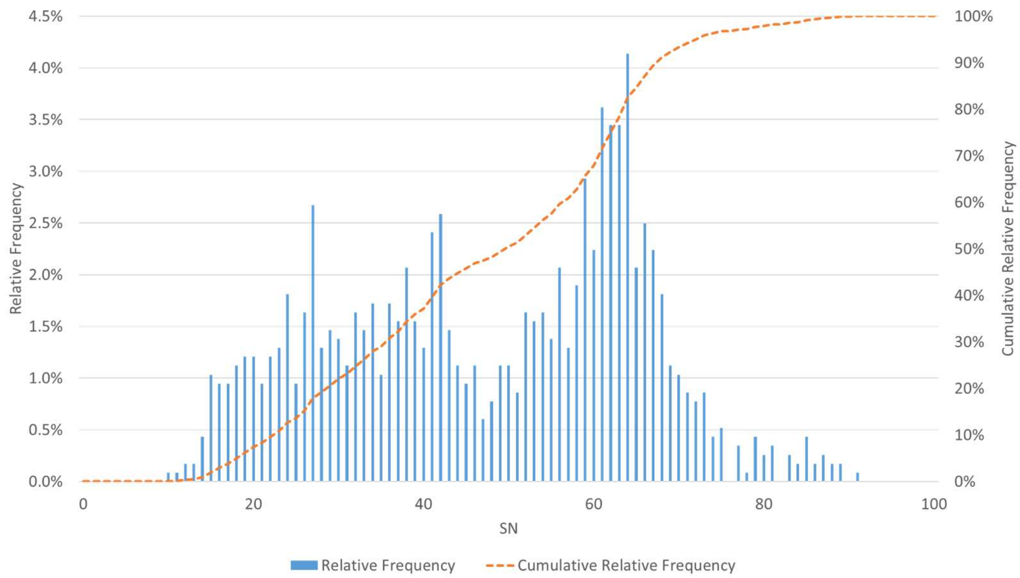

Figure 8: Relative Frequency and Cumulative Relative Frequency of SN of the Sample

Define Condition States for Skid Number

Table 1 shows the six condition states in terms of SN defined for this case study. The SN boundaries for each condition state were established based on previous work conducted (Wu, Zhang, Long, & Murphy, 2014) and the data available for this study.

Table 1: Condition States Defined for the Case Study

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

Estimate Deterioration Transition Probability Matrix

The training and test datasets were selected using the Holdout procedure with 70 percent of the data in the training dataset and 30 percent in the test dataset. Subsequently, the TPM was estimated using the training dataset according to Equation 6, and then the future conditions of skid resistance for the training dataset were predicted using Equation 7. The prediction was performed for years 2013, 2014, and 2015. Finally, the TPM was optimized by reducing the differences between the skid resistance condition predicted and observed for the training dataset using Equation 8. The resulting optimized TPM is presented in Table 2.

Table 2: Optimized TPM for the Training Dataset

Condition States	**1**	**2**	**3**	**4**	**5**	**6**
1	0.848	0.026	0.125	0.000	0.000	0.000
2	0.000	0.916	0.000	0.048	0.000	0.037
3	0.000	0.000	0.852	0.000	0.148	0.000
4	0.000	0.000	0.000	0.893	0.100	0.007
5	0.000	0.000	0.000	0.000	0.843	0.157
6	0.000	0.000	0.000	0.000	0.000	1.000

As can be seen from Table 2, skid resistance deterioration rates are higher for condition states 2, 3, and 4. Furthermore, in these condition states there is a percentage of pavement sections that skips one condition state. For example, for condition state 3, around 15 percent of the pavement sections would deteriorate directly to state 5, skipping state 4. In other words, the SN deterioration in this case do not transit through all the states before reaching the last state, being closer to a progressive TPM (Equation 4) than a Sequential TPM. Therefore, the TPM presented in Table 2 was used for the rest of the analysis, and it was not optimized as a sequential TPM.

Perform a Statistical Test of the Prediction

Using the optimized TPM obtained in the previous phase, the pavement skid condition of the network was predicted for both the training and test datasets. In this case study, the base year was 2012, and the pavement skid condition prediction was performed for the years of 2013, 2014, and 2015. Subsequently, the Chi-Square test was applied to the predicted pavement skid condition for both the training and the test dataset. The α value for the Chi-Square test was set to 0.05.

Results of Numerical Case Study

Table 3 presents the results of the Chi-Square test for both the training and test dataset. As can be seen from this table, the differences between the predicted pavement skid condition and the observed pavement skid condition were not significant ($p = 0.09 > \alpha$). Similarly, the differences between the predicted pavement skid condition and the observed pavement skid condition for the test dataset were not significant either ($p = 0.36 > \alpha$), even when this dataset was not included in the estimation of the TPM. Therefore, it can be concluded that the MC predicted the pavement skid condition for both datasets within an acceptable range of difference. Table 4 and Table 5 present the summary of pavement sections observed and predicted for both the training and test datasets, with the corresponding state probabilities for each condition state.

Table 3: Results of the Chi-Square Statistical Test to Assess the Deterioration Model

	Training Dataset Results	**Test Dataset Results**
Degrees of Freedom (DF)	10	10
Significance Level (α)	0.05	0.05
Right Tail Critical Value of the Chi-Square Test for 10 DF	18.307	18.307
Chi-Square Test Result Obtained	16.205	11.02
Probability of the Chi-Square Test Result (p)	0.09	0.36

Table 4: Pavement Sections Observed and Predicted for the Training Dataset, from 2012 to 2015, with the Corresponding Probabilities

Training Dataset	**Condition States**											
Year	**1**		**2**		**3**		**4**		**5**		**6**	
	Obs.	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**
2012 (Base Year)	259 (0.312)	(NA)	266 (0.320)	(NA)	125 (0.150)	(NA)	70 (0.084)	NA	52 (0.063)	(NA)	59 (0.071)	(NA)
2013	210 (0.253)	219.6 (0.264)	247 (0.297)	250.4 (0.301)	157 (0.189)	139 (0.167)	74 (0.089)	75.2 (0.091)	65 (0.078)	69.4 (0.083)	78 (0.094)	77.5 (0.093)
2014	165 (0.199)	186.2 (0.224)	257 (0.309)	235 (0.283)	128 (0.154)	146 (0.176)	78 (0.094)	79.2 (0.094)	96 (0.116)	86.6 (0.104)	107 (0.129)	98.1 (0.118)
2015	179 (0.215)	157.8 (0.190)	205 (0.247)	220.1 (0.265)	153 (0.184)	147.7 (0.178)	83 (0.100)	81.9 (0.099)	97 (0.117)	102.6 (0.123)	114 (0.137)	120.9 (0.145)

NOTES: (1) **NA** represents Not Applicable; (2) **Obs.** represents observed number of pavement sections for each skid condition state, with the corresponding state probability in parenthesis; (3) **Est.** represents predicted number of pavement sections for each skid condition state, with the corresponding state probability in parenthesis; (4) Numbers in the parentheses are the corresponding state probabilities.

Table 5: Pavement Sections Observed and Predicted for the Test Dataset, from 2012 to 2015, with the Corresponding Probabilities

Test Dataset	**Condition States**											
Year	**1**		**2**		**3**		**4**		**5**		**6**	
	Obs.	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**	**Obs.**	**Est.**
2012 (Base Year)	113 (0.342)	(NA)	91 (0.276)	(NA)	51 (0.155)	(NA)	28 (0.085)	(NA)	20 (0.061)	(NA)	27 (0.082)	(NA)
2013	92 (0.279)	93.1 (0.282)	91 (0.276)	93.8 (0.284)	51 (0.155)	54.2 (0.164)	36 (0.109)	28 (0.085)	30 (0.091)	28.2 (0.085)	30 (0.091)	32.8 (0.099)
2014	73 (0.221)	79 (0.239)	88 (0.267)	90.8 (0.275)	59 (0.179)	56.4 (0.171)	27 (0.082)	30.4 (0.092)	35 (0.106)	33.8 (0.102)	48 (0.145)	39.7 (0.120)
2015	77 (0.233)	68.4 (0.207)	79 (0.239)	85.3 (0.259)	53 (0.161)	57.5 (0.174)	37 (0.112)	32.8 (0.099)	34 (0.103)	38.8 (0.118)	50 (0.152)	47.1 (0.143)

NOTES: (1) **NA** represents Not Applicable; (2) **Obs.** represents observed number of pavement sections for each skid condition state, with the corresponding state probability in parenthesis; (3) **Est.** represents predicted number of pavement sections for each skid condition state, with the corresponding state probability in parenthesis; (4) Numbers in the parentheses are the corresponding state probabilities.

Figure 9 and Figure 10 present a visual comparison of the predicted and observed proportions for each condition state for the training set and testing set respectively. These figures present the proportions predicted and observed. A perfect model will have all the points over the diagonal line. On the other hand, a poor model will have points all the points scattered. As can be seen in these two figures, the points are closer to the diagonal line for all the years of the analysis.

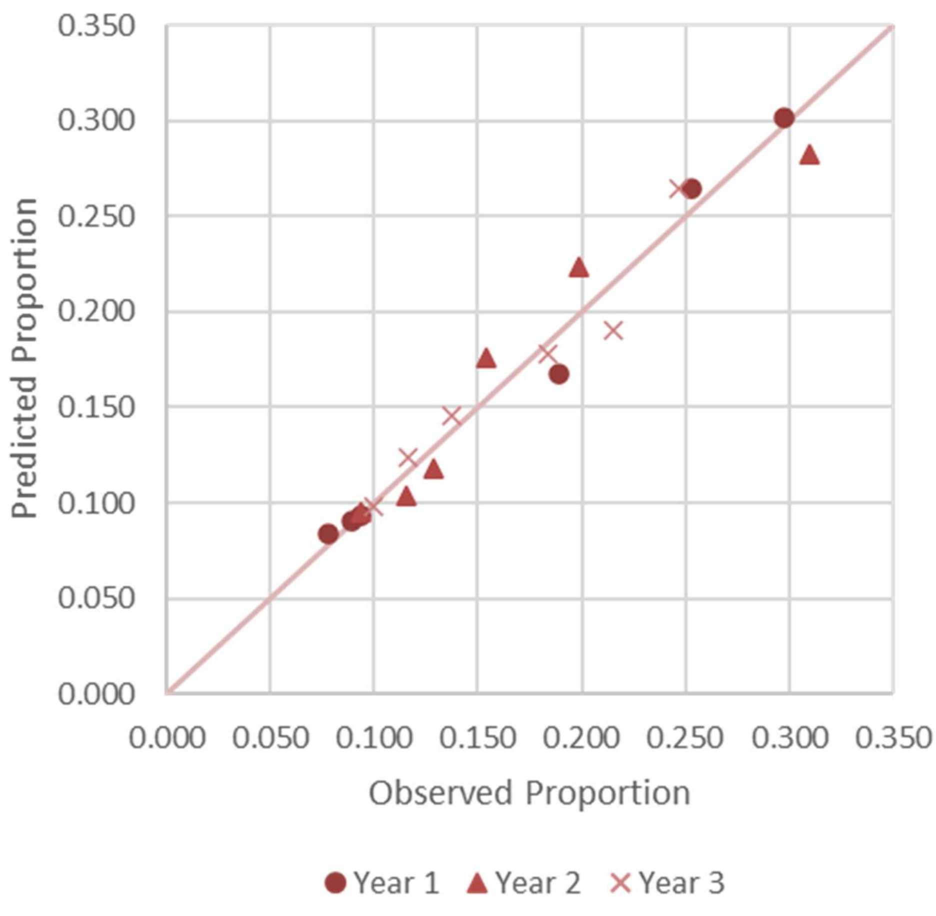

Figure 9: Comparison of the Predicted and Observed Proportions For Each Condition State of the Training Set, Years 2013-2015

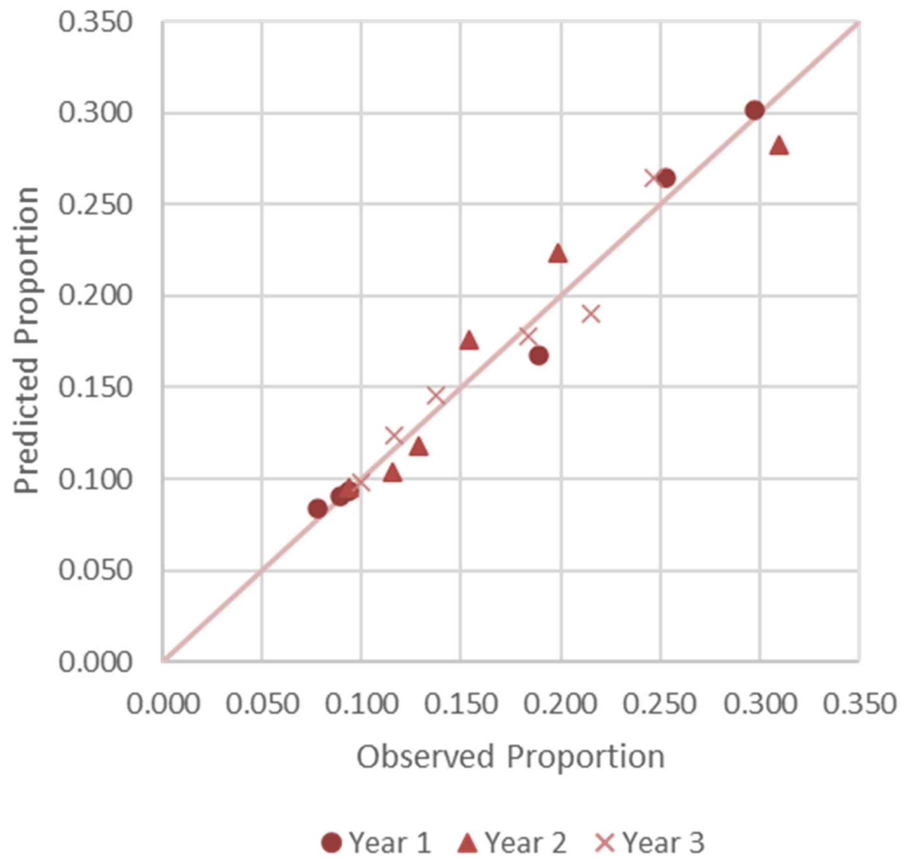

Figure 10: Comparison of the Predicted and Observed Proportions For Each Condition State of the Testing Set, Years 2013-2015

Despite the site-specific conditions of each pavement section, the result suggests that a general deterioration model can be developed for skid resistance at the network level. Thus, the MC process can serve as a viable approach to modelling SN deterioration for pavement networks where physical models cannot be used because of lack of site-specific information such as aggregate properties. This ability to predict SN at the network level allows a highway agency to develop a Maintenance and Rehabilitation (M&R) budget plan for managing the skid resistance of its pavement network. For example, each TXDOT

District is required to develop a four-year plan for managing its pavement condition. The current four-year plans consider only the pavement Condition Score (CS) (Liu, Jaipuria, Murphy, & Zhang, 2012). The proposed model can be used to estimate the future percentage of pavement sections in the network with SN greater than 25 during the four-year planning process if no treatment is applied. More specifically, based on the case study data, Table 5 presents the observed percentage of pavement sections with SN greater than 25 between 2012 and 2015, and the predicted SN for the four-year planning period of 2016 to 2019. With a given SN target and by knowing how the skid resistance of the pavement network deteriorates in terms of SN, transportation agencies can estimate its budget needs for the four-year planning horizon.

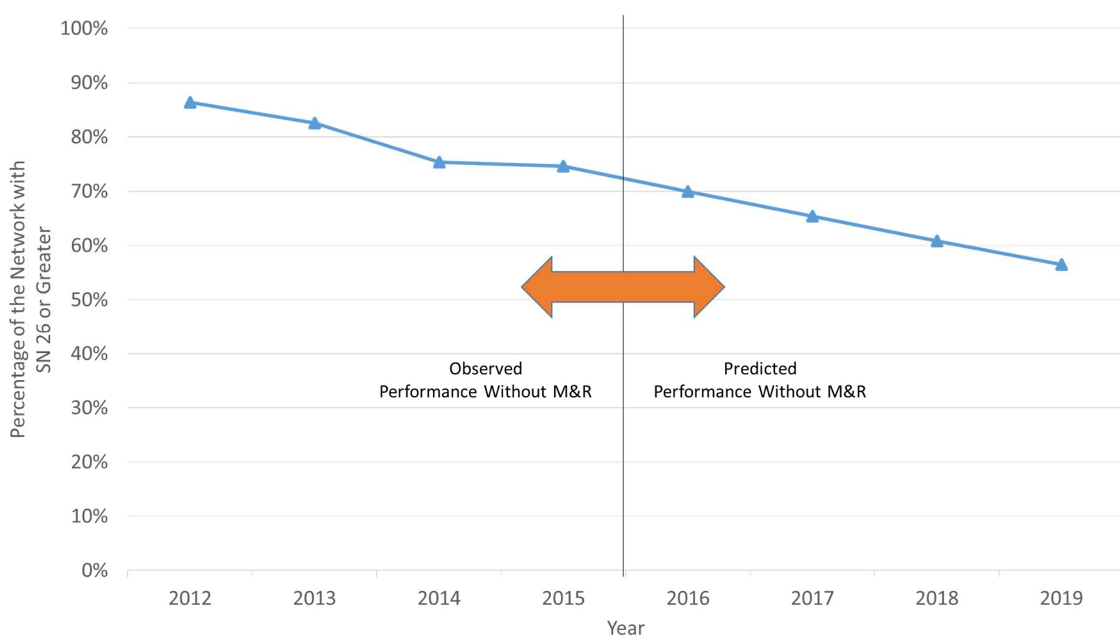

Figure 11: Percentage of the Network with SN greater than 25 that is Observed between 2012 and 2015, and Predicted between 2016 and 2019 If No Treatment Is Applied

2.5 Conclusions

This study proposed a framework for modeling pavement skid resistance at the network level. The framework is comprised of three major components: (a) pre-process SN data, (b) estimate TPM, and (c) perform a statistical test of the predictions. The applicability of the methodological framework was demonstrated with the case study using skid data from the Austin District of the Texas Department of Transportation (TxDOT). The major conclusions drawn from this study include:

- There is a proven relationship between the number of crashes and pavement Skid Number (SN), where low SN could lead to a higher number of crashes. For this reason, transportation agencies and researchers have considered managing pavement skid resistance, including the development of deterioration models to predict the future SN values of pavements.
- Markov Chain processes can be effectively used to model pavement skid resistance deterioration at the network level. In particular, Skid Number data collected using the ASTM E274/E274M-15 was predicted using the proposed framework within an acceptable accuracy. However, it is important to note that this model was acceptable for a 4-year period, and should not be used for long-term prediction.
- The proposed Markov Chain process for skid resistance prediction can be used by state and local agencies to predict deterioration rates of skid resistance in a network and anticipate skid resistance budget needs.

Chapter 3: Estimating the Benefit-Cost Ratio of Establishing SN Intervention Thresholds at the Network Level

In Chapter 2, the feasibility of using Markov Chains to model SN deterioration was tested. In this chapter, a more robust cross-validation methodology is used to validate the MC model, and a larger database is used to develop deterioration models for Interstate Highways, Urban Freeways and Arterials and Collectors. In this chapter the methodology to quantify the BCR of establishing SN intervention thresholds for roadway networks is developed. Benefits are estimated in terms of the monetary value of crash reductions. Costs are estimated by considering a) the cost for treating pavement sections, b) the monetary value of travel time delays, and c) the monetary value of road safety risks associated with work zones.

This chapter contains extracts from a manuscript that has been published and is available in INTERNTATIONAL JOURNAL OF PAVEMENT ENGINEERING, December 1st, 2020, http://tandfonline.com/10.1080/10298436.2020.1847284[2]

[2] Galvis Arce, O. D., & Zhang, Z. (2020). Framework to Estimate the Benefit-Cost Ratio of Establishing Minimum Pavement Friction Levels for Roadway Networks. *International Journal of Pavement Engineering*. doi:10.1080/10298436.2020.1847284
Author contributions: study conception and design: Galvis Arce, O.D., Zhang, Z.; data collection: Galvis Arce, O.D.; analysis and interpretation of results: Galvis Arce, O.D., Zhang, Z.; draft manuscript preparation: Galvis Arce, O.D. All authors reviewed the results and approved the final version of the manuscript.

3.1 METHODOLOGICAL FRAMEWORK

The primary objective of this study is to provide a methodology to estimate the BCR of establishing an intervention threshold for pavement friction at the network level. The methodological framework comprises three components: (a) the development of a skid resistance deterioration model, (b) the estimation of the costs due to skid resistance treatments, and (c) the monetary value of crash reductions resulted from skid resistance improvement. The framework is depicted in Figure 12.

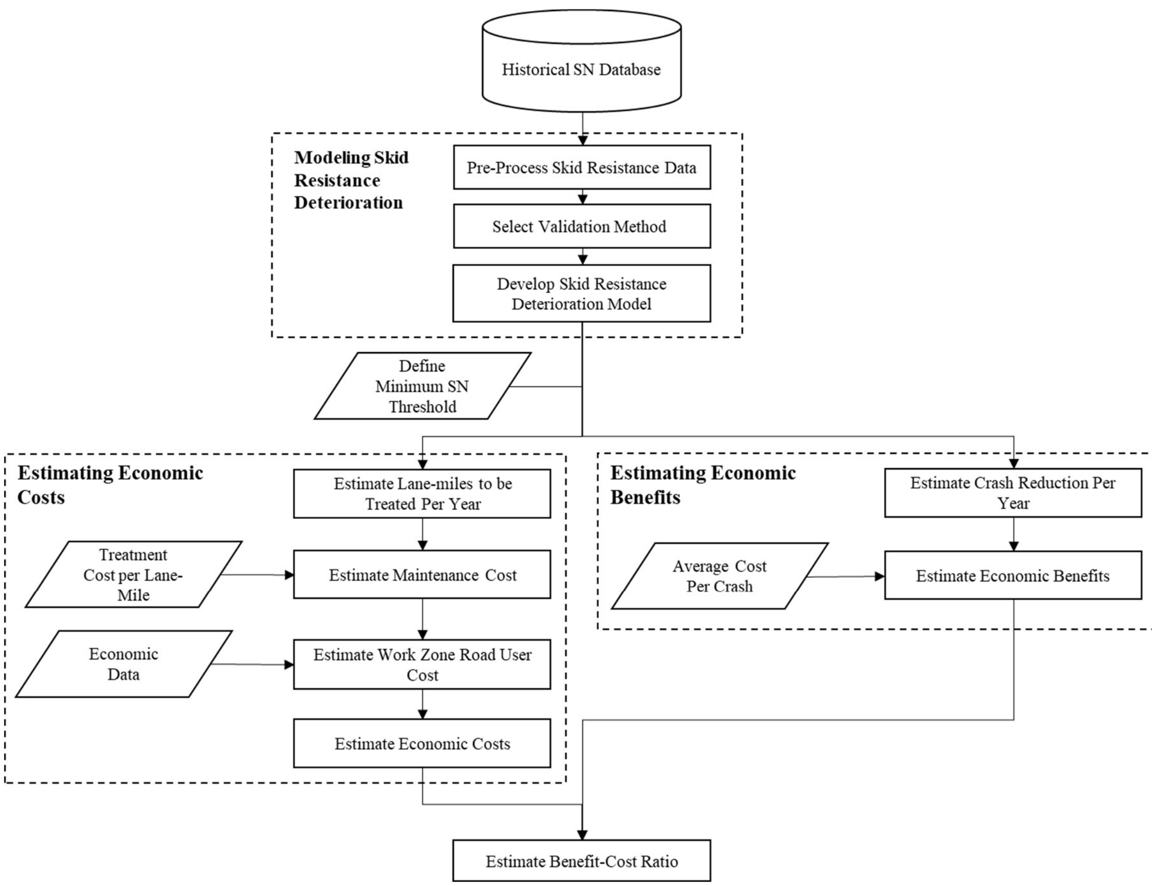

Figure 12: Framework for the Estimation of the Benefit-Cost Ratio of Establishing a Friction Intervention Threshold

Modeling Skid Resistance Deterioration

The deterioration model is the tool used to model future condition in the network. In this study, the Markov Chain (MC) model is selected to model the deterioration due to its adaptability to incorporate the historical SN data available and the maintenance actions. There are four key concepts in this model: 1) the condition states, 2) the Deterioration Transition Probability Matrix (denoted as $\boldsymbol{P}$), 3) the condition vector $\boldsymbol{u}$, and 4) the Maintenance Transition Probability Matrix (denoted as $\boldsymbol{M}$). The condition states and the matrix $\boldsymbol{P}$ are explained in Chapter 2. The condition vector $\boldsymbol{u}$ and the matrix $\boldsymbol{M}$ are discussed in details as follows.

The condition vector $\boldsymbol{u}$ is the proportion of the network in each condition state. For instance, 20 percent of the network could be in condition state 1, 15 percent could be in condition state 2, etc. The size of $\boldsymbol{u}$ is r.

The Maintenance Transition Probability Matrix ($\boldsymbol{M}$) contains the annual probabilities that the SN of a pavement will improve from a worse condition to a better condition after a treatment. In general, $\boldsymbol{M}$ follows the matrix presented in Equation 10 (Panthi, 2009). The m_{ii} values represent the proportion of the network that are not treated. The m_{ij} values where $i > j$ represent the proportion of the network that are treated and will improve their SN from a worse condition i to a better condition j. Similar to the matrix $\boldsymbol{P}$, other properties of $\boldsymbol{M}$ are that $0 \leq m_{ij} \leq 1$ and $\sum_{j=1}^{r} m_{ij} = 1$.

$$\boldsymbol{M} = \begin{bmatrix} m_{11} & 0 & \cdots & 0 \\ m_{21} & m_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ m_{r1} & m_{r2} & \cdots & m_{rr} \end{bmatrix} \tag{10}$$

The vector $\boldsymbol{u}$ and the matrices $\boldsymbol{P}$ and $\boldsymbol{M}$ are used to estimate the future condition of the network when there is a treatment.

$$\boldsymbol{u}_k = \boldsymbol{u}_{\boldsymbol{0}} * (\boldsymbol{M} * \boldsymbol{P})^k \tag{11}$$

Where:

$\boldsymbol{u}_k$ = Condition vector at year k.

$\boldsymbol{u}_{\boldsymbol{0}}$ = Initial condition vector.

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

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

Pre-Process Skid Resistance Data

The historical SN database is used to assess the data available for the analysis. Pavement sections should be grouped in categories with similar skid resistance deterioration and have distinct models. Some of the known factors that impact SN deterioration are pavement type, local weather, and traffic levels (Echaveguren, Solminihac, & Chamorro, 2010; Smith, Knighton, & Guthrie, 2016).

The next step is to define the condition states for the Markov Chain Process. The condition states are established by discretizing of the skid resistance condition using the SN value (for example, condition 1 could be defined from SN 50 to SN 100). The definition of the condition states faces a trade-off between data available and the accuracy needed for the model. Models with more condition states (or, in other words, smaller value range for each condition state) require more data but their prediction is more precise. However, because of data availability issues, often times the ranges of the condition states need to be large enough so that there is sufficient data for each condition state (Thompson, et al., 2012).

Select Validation Method

There are various methods to validate the deterioration model such as the Holdout, K-Fold Cross Validation, Random Subsampling, or Bootstrap. In general, these methods use a portion of the data for training the model (that is, estimate the parameters of the model) and the remaining portion of the data for validating the accuracy of the model. In this paper, 80 percent of the SN data was randomly selected to train the model, and the 20 percent was used to validate the accuracy of the model.

For training the model (80 percent of the data), the K-Fold Cross-Validation technique is used. This technique consists in dividing the data into K equal sized groups. Subsequently, for one iteration, the data of $K-1$ groups are used for training the model and the remaining data is used for testing (Figure 13). This process is repeated K times, each time changing the data that is tested Figure 7. In this paper, K equals 4. After K iterations, the matrix $\boldsymbol{P}$ is estimated.

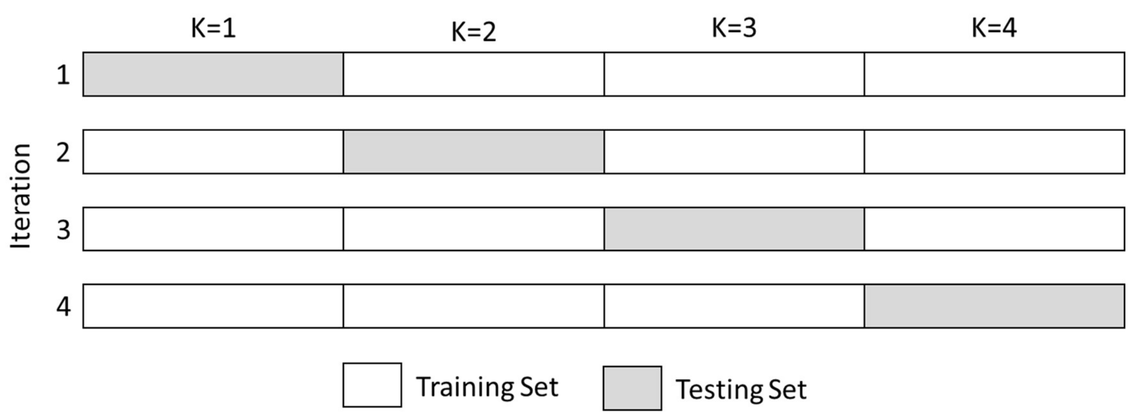

Figure 13: Example of the K-Fold Cross-Validation For K=4

For validating the model (the remaining 20 percent of the data), the Chi-Square (χ^2) Goodness-of-fit test is used. The purpose of this validation step is to assess the accuracy of the model with new data that was not used to train the model.

Develop Skid Resistance Deterioration Model

First, the dataset is split in the training dataset (80 percent of the data) and the validation dataset (20 percent of the data). The training dataset is further split following the K-Fold Cross-Validation procedure. In each iteration, the values p_{ij} of $\boldsymbol{P}$ are estimated using the 'counting proportions' formula (Equation 6) (Galvis Arce & Zhang, Skid Resistance Deterioration Model At the Network Level Using Markov Chains, 2019). The parameters of the matrix $\boldsymbol{P}$ are the average of the K estimations.

Previous researchers have found that the accuracy of the prediction of $\widehat{\boldsymbol{P}}$ can be improved using optimization (Butt, Shahin, Feighan, & Carpenter, 1987; Jiang, Saito, & Sinha, 1989; Galvis Arce & Zhang, Skid Resistance Deterioration Model At the Network Level Using Markov Chains, 2019). The optimization objective is to minimize the error between the observed values of the testing set and the predicted values estimated using Equation 7. The objective function used in this paper is presented in Equation 12. The Generalized Reduced Gradient (GRG) Non-linear algorithm, which is included in Microsoft® Excel, was used to optimize Equation 12.

$$Min \sum_{k=1}^{4} \sum_{i=1}^{r} \frac{\left(\boldsymbol{u}_{i,k} - \widehat{\boldsymbol{u}}_{i,k}\right)^2}{\widehat{\boldsymbol{u}}_{i,k}} \qquad (12)$$

Where:

$\boldsymbol{u}_{i,k}$ = Observed condition state probability i of the testing set at iteration k.

$\widehat{\boldsymbol{u}}_{i,k}$ = Predicted condition state probability i of the testing set at iteration k.

r = Total number of condition states.

Finally, the model is validated using the validation dataset (the 20 percent of the original data). This dataset is used to validate the accuracy of the prediction because it was not used to train the model; therefore, it is considered as new data. Using the optimized matrix $\widehat{\boldsymbol{P}}$, the future condition of the validation dataset is estimated using Equation 7. Then, the Chi-Square (χ^2) statistic is estimated according to Equation 9.

For the Chi-Square (χ^2) Goodness-of-Fit test, the null hypothesis (H_0) is that there is no significant difference between the observation and the prediction. In this paper, α is set to 0.05. Therefore, if the p-value of the test is smaller than α, H_0 is rejected and, thus, the model would not satisfy the minimum of accuracy expected. Otherwise, the model is performing at a reasonable accuracy level. The higher the p-value the higher the accuracy level.

Estimating Economic Costs

The maintenance costs are estimated as the budget needed to treat the pavement sections for which friction levels drop below the intervention threshold. The deterioration model is used to estimate the number of pavement sections in lane miles that will require a treatment during the analysis period.

Estimate the Lane Miles to Be Treated per Year

The initial condition vector $\boldsymbol{u_0}$ and the matrices $\boldsymbol{P}$ and $\boldsymbol{M}$ are used to estimate the future condition of the network. The matrix $\boldsymbol{M}$ is defined based on the treatment applied and the intervention SN threshold defined (the threshold in which an action is taken). One assumption that is implicit in Equation 11 is that the treated pavements will deteriorate at the same rate as those untreated pavements; however, in reality, treated pavements deteriorate at a lower rate than the untreated pavements for the first years. Therefore, this is a conservative estimation because it partially reduces the life service of the treatments, but it is a reasonable assumption because skid resistance treatments do not last long compared to the pavement life. Once the future condition of the network is estimated, the lane miles to be treated are estimated as shown in Equation 13.

$$LM_k = \sum_{i=1}^{r} \sum_{j=1}^{i-1} m_{ij} * u_{k,i} * L \tag{13}$$

Where:

LM_k = Number of lane miles to be treated in year k.

$\sum_{i=1}^{r}$ = Sum over all the condition states.

$\sum_{j=1}^{i-1} m_{ij}$ = Proportion of the network in condition state i to be treated in year k.

$u_{k,i}$ = Proportion of the network in condition state i in year k.

L = Total number of lane miles in the network.

Estimate the Maintenance Costs

The annual maintenance costs are estimated as the product of the number of lane miles to be treated and the average cost of the treatment per lane mile as shown in Equation 14. This average cost is a representative value of the treatment costs per lane mile in the network.

$$CO_k = LM_k * UCT \tag{14}$$

Where:

CO_k = Maintenance costs in year k.

LM_k = Number of lane miles to treat in year k.

UCT = Unit cost of the treatment per lane mile.

Estimate the Work Zone Road User Costs

In order to treat a pavement section, it is necessary to prepare the section that is affected as a work zone. This causes that the normal traffic flow on the road would be affected (for instance, when there is a lane closure in a highway due to the application of a seal coat). Therefore, besides the direct maintenance costs of the treatments, there are other indirect costs that are absorbed by the road users. These indirect costs are defined as "Work Zone Road User Costs" (WZ RUC) (FHWA, 2011).

Although the type of impacts depends on the type of work to be performed, in general WZ RUC can be categorized as mobility, safety, noise, and environmental impacts. Some of these costs are easier to monetarize while others are more difficult and can be described qualitatively only (FHWA, 2011). Moreover, some of these costs are site-specific and there is not a general methodology to estimate them (FHWA, 2011). Because the scope of this paper is to estimate the BCR at the network level, only network level travel delay costs, depreciation costs and road safety costs are estimated.

Travel Delay and Depreciation Costs.

These costs are associated to the additional time due to the impact on traffic flow in the presence of work zones. These costs were estimated using the methodology developed by the Federal Highway Administration (FHWA, 2011). The process is summarized as follows:

1. **Estimate Work Zone Delay Time per Vehicle:** The delay time is the sum of the additional time to cross the work zone, stopping time (if any), and queue delay time (if any). Some of these values (for instance, queue delay time) are site-specific and depend on the number of lanes and traffic. Therefore, at the network level, only the additional time that each vehicle will require to cross the work zone is considered in the analysis.
2. **Estimate the Work Zone Travel Delay Costs per Day:** This cost is associated with the delay time. The basic principle is that the time lost could have been spent

in a productive way, either working or recreating (FHWA, 2011). In this paper, four categories are analyzed: 1) personal travel (passenger cars), 2) business travel (passenger cars), 3) single-unit truck traffic (vehicle classes 4 through 7), and 4) combination of trucks (vehicle classes 8 through 13). Figure 14 presents the process to estimate the Work Zone Travel Delay Costs per Day for each category and Table 6 presents the sources of information used in this paper. When possible, the researchers can use local or state information to increase the accuracy of the estimation; therefore, the methodology is not applicable to United States only.

3. **Estimate Depreciation Costs due to Travel Time Delay:** This cost is associated with the delay time. This cost represents the additional depreciation cost due to time delays in the presence of work zones. In this paper, three categories are analyzed: 1) passenger cars, 2) single-unit truck traffic (vehicle classes 4 through 7), and 3) combination of trucks (vehicle classes 8 through 13). Figure 15 presents the process to estimate depreciation costs per day for each category and Table 6 presents the sources of information used in this paper. When possible, the researchers can use local or state information to increase the accuracy of the estimation.

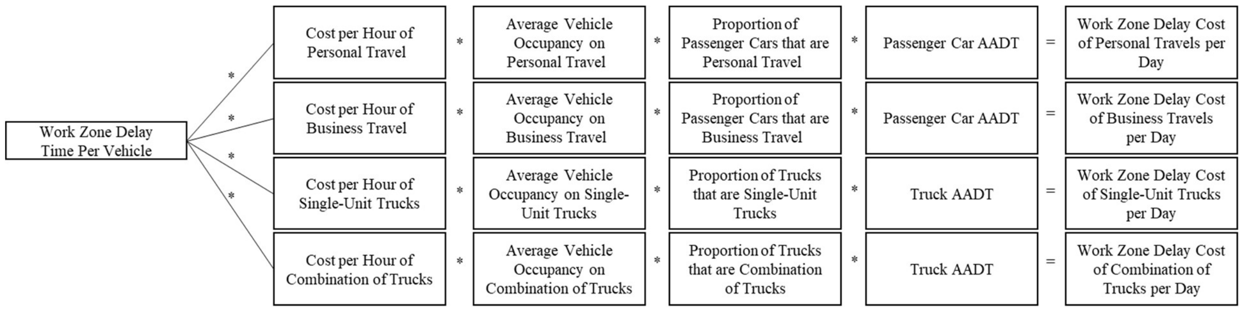

Figure 14: Process to Estimate the Work Zone Delay Cost for 1) Personal Travel, 2) Business Travel, 3) Single-Unit Trucks, and 4) Combination of Trucks.

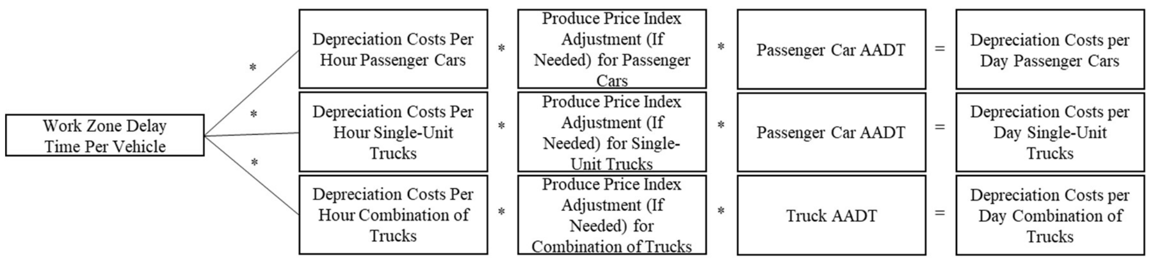

Figure 15: Process to Estimate the Depreciation Costs for 1) Passenger Cars, 2) Single-Unit Trucks, and 3) Combination of Trucks

Table 6: Sources and Formulas (If Applied) To Estimate the Work Zone Delay and Depreciation Costs

Item	**Source**	**Specific Source**	**Formula (If Applies)**	**Value**
Cost per Hour of Personal Travel	U.S. Census Bureau (2018) American Community Survey Briefs	Median Household Income from the American Community Survey Briefs by state	Local: 50% of median household annual income / 2,080 hours ($2017) Intercity: 70% of median household annual income / 2,080 hours ($2017)	Local: $14.23 Intercity: $19.93
Cost per Hour of Business Travel	U.S. Bureau of Labor Statistics - Occupational Employment Statistics (2018) and Employer Costs for Employee Compensation Summary (2020)	Median hourly wages and benefits of all civilian workers by state	100% of the median hourly wages and benefits ($2017)	$26.12
Cost per Hour of Single-Unit Trucks	U.S. Bureau of Labor Statistics - Occupational Employment Statistics (2018) and Employer Costs for Employee Compensation Summary (2020)	Median hourly wages and benefits of category "Light Truck or Delivery Services Drivers" by state	100% of the median hourly wages and benefits ($2017)	$23.08
Cost per Hour of Combination of Trucks	U.S. Bureau of Labor Statistics - Occupational Employment Statistics (2018) and Employer Costs for Employee Compensation Summary (2020)	Median hourly wages and benefits of category "Heavy and Tractor-Trailer Truck Drivers" by state	100% of the median hourly wages and benefits ($2017)	$28.13
Average Vehicle Occupancy on Personal Travel	FHWA (2018) National Household Travel Survey	Average Vehicle Occupancy, "All Purposes"	None	1.67
Average Vehicle Occupancy on Business Travel	FHWA (2018) National Household Travel Survey	Average Vehicle Occupancy, "To/From Work"	None	1.18
Average Vehicle Occupancy on Single-Unit Trucks	FHWA (2011) Work Zone Road User Costs	National Averages	None	1.05

Table 6, continued

Item	Source	Specific Source	Formula (If Applies)	Value
Average Vehicle Occupancy on Combination of Trucks	FHWA (2011) Work Zone Road User Costs	National Averages	None	1.12
Proportion of Passenger Cars that are Personal Travel	Bureau of Transportation Statistics (2020)	"Transportation by the Numbers" report per state, passenger travel by trip purpose	None	98.50%
Proportion of Passenger Cars that are Business Travel	Bureau of Transportation Statistics (2020)	"Transportation by the Numbers" report per state, passenger travel by trip purpose	None	1.50%
Proportion of Trucks that are Single-Unit Trucks	FHWA (2020) Highway Performance Monitoring System (HPMS) Sample	Average Single-Unit Trucks as a proportion of Truck AADT by Functional System Class	None	Estimated for the case study
Proportion of Trucks that are Combination of Trucks	FHWA (2020) Highway Performance Monitoring System (HPMS) Sample	Average Combination of Trucks as a proportion of Truck AADT by Functional System Class	None	Estimated for the case study
Passenger Car AADT	Local sources	Obtained from sections analyzed	None	Estimated for the case study
Truck AADT	Local sources	Obtained from sections analyzed	None	Estimated for the case study
Depreciation Costs Per Hour Passenger Cars	FHWA (2011) Work Zone Road User Costs	Depreciation costs per hour for medium-sized to large autos ($2010)	None	$1.40
Depreciation Costs Per Hour Single-Unit Trucks	FHWA (2011) Work Zone Road User Costs	Depreciation costs per hour for four-tire single-unit trucks ($2010)	None	$2.58

Table 6, continued

Item	**Source**	**Specific Source**	**Formula (If Applies)**	**Value**
Depreciation Costs Per Hour Combination of Trucks	FHWA (2011) Work Zone Road User Costs	Depreciation costs per hour for 5+ axles trucks ($2010)	None	$8.70
Produce Price Index Adjustment (If Needed) for Passenger Cars	U.S. Bureau of Labor Statistics (2020b) Produce Price Index	PPI for passenger cars (Item # 141101)	PPI2014 / PPI2010	0.9262
Produce Price Index Adjustment (If Needed) for Single-Unit Trucks	U.S. Bureau of Labor Statistics (2020b) Produce Price Index	PPI for trucks, 14,000 lbs. and under (Item # 141105)	PPI2014 / PPI2010	1.2093
Produce Price Index Adjustment (If Needed) for Combination of Trucks	U.S. Bureau of Labor Statistics (2020b) Produce Price Index	PPI for trucks, over 14,000 lbs. GVW (Item # 141106)	PPI2014 / PPI2010	1.0030

Safety Costs.

Safety costs are associated with the increase in crash rates due to the presence of work zones. A network level estimation can be performed using a Crash Modification Factor (CMF). This CMF is applied for the length of the highway with presence of work zones. The safety costs are estimated as shown in Equation 15. A component of Equation 15 is the Average Cost per Crash (ACC). The ACC is estimated taking into account the KABCO scale, which is used by TxDOT to classify the different types of injuries (Equation 16).

$$C_{Safety} = R * (CMF_{WZ} - 1) * VMT * ACC \tag{15}$$

Where:

C_{Safety} = Safety costs due to the presence of work zones.

R = Crash rate per million VMT before the presence of work zones.

CMF_{WZ} = Crash Modification Factor due to the presence of work zones.

VMT = Average traffic VMT (in million) of the section of the highway with presence of work zones.

ACC = Average cost per crash.

$$ACC = \left(\sum_{s=K,A,B,C,O} U_s * A_s \right) / CR \tag{16}$$

Where:

ACC = Average cost per crash.

U_s = Unit cost of crash severity s, using the KABCO scale.

A_s = Number of people killed or injured with crash severity s (number of crashes in case of property-damage crashes or unknown if people injured).

CR = Total number of crashes in the network.

Estimating Economic Benefits

The economic benefits are estimated as the monetary value of crash reductions. These crash reductions can be achieved by treating pavement sections when their friction levels fall below the minimum threshold. Crash reductions can be estimated in two ways. One way is to use a model to quantify the expected number of crashes as a function of the SN. For instance, a model where crash rates per 100 million Vehicle-Kilometer are a function of SCRIM coefficient can be used to estimate the crash rates in each condition state (Davies, Cenek, & Henderson, 2005). Another way is to estimate the crash rates for each condition state using historical data. In this paper, crash rates per million VMT for each condition state are estimated using historical data.

Estimate Crash Reduction Per Year

Once the crash rates per million VMT for each condition state (R_i) are estimated using historical data or developed models, these rates are used with the future condition of the network (obtained from the MC model) to estimate the expected number of crashes. The base scenario is the expected number of crashes if the pavement friction is not improved at all. The second scenario is the expected number of crashes if the pavement friction is improved when the pavement SN has a value equal or below the minimum threshold. Both scenarios are calculated as shown in Equation 17.

$$CR_k = \sum_{i=1}^{r} (\widehat{\boldsymbol{u}_{k,\iota}} * N * R_i * AvgVMT) \tag{17}$$

Where:

CR_k = Expected number of crashes in the network in year k.

r = Total number of condition states.

$\widehat{\boldsymbol{u}_{k,\iota}}$ = Proportion of the network in condition state i in year k.

N = Total number of sections.

R_i = Crash rate per million VMT for condition state i.

$AvgVMT$ = Average traffic VMT (in million).

Estimate the Economic Benefits

The annual economic benefits are estimated as the product of *a*) the expected reduction of crashes in the network, and *b*) the average cost per crash (Equation 18).

$$BE_k = (CR_k - CR_k^{SN}) * ACC \quad (18)$$

Where:

BE_k = Economic benefits of crash reduction in year k.

CR_k = Expected number of crashes in the network in year k if pavement friction is not improved.

CR_k^{SN} = Expected number of crashes in the network in year k if pavement friction is improved when the pavement SN reaches a value equal or below the minimum threshold.

ACC = Average cost per crash.

Estimate Benefit-Cost Ratio

The Benefit-Cost Ratio (BCR) is estimated as the ratio of the benefits and costs during the service life of the treatment. In this paper, the service life of the treatment is defined according to the procedure outlined in the NCHRP Report 713 "Estimating Life Expectancies of Highway Assets" for Markov Chain models (Thompson, et al., 2012). In this procedure, the service life is defined as the period of time between the treatment and an estimated 50 percent of probability of reaching a 'failing' condition state (a condition state where it is considered that there is no longer a treatment).

Once the service life is defined, two adjustments are performed to the annual benefits and costs according to the U.S. DOT "Benefit-Cost Analysis Guidance for Discretionary Grant Programs" (U.S. DOT, 2020). The first adjustment accounts for inflation using historical data (or the average inflation rate in the case of future years). The second adjustment accounts for the time value of money (adjustment rate of 7 percent per year). Once the values are adjusted, the BCR is estimated as shown in Equation 19.

$$BCR^{SN} = \frac{\sum_{k=1}^{T} BE_k}{\sum_{k=1}^{T} CO_k} \tag{19}$$

Where:

BCR^{SN}= Benefit-Cost Ratio of establishing a minimum SN threshold.

T = Total number of years of the analysis period.

BE_k = Economic benefits of crash reduction in year k.

CO_k = Maintenance costs in year k.

3.2 Numerical Case Study

Dataset Description

The Skid Number dataset for the case study was obtained from the Austin District of the Texas Department of Transportation (TxDOT). Annual SN measurements were extracted for asphalt pavement sections without SN improvements from 2000 to 2015. A total of 52,097 pavement sections were used to develop the skid resistance deterioration model. A subset of 993 pavement sections with recorded SN between 2012 and 2015 were used to estimate the Benefit-Cost Ratio. This subset represents 9.9 percent of the total number of pavement sections in the Austin District and a total of 1,165.4 lane miles.

Modeling Skid Resistance Deterioration

Skid Number deterioration was analyzed by traffic AADT and Functional System Class in order to define homogenous groups of deterioration. It was found that groups classified by AADT did not yield significant changes in the deterioration rate while distinct skid deterioration trends were observed when the Functional System Class was used as the classifier. More specifically, three distinct deterioration trends were observed for the following functional system groups as shown in Figure 16: 1) Interstate Highways, 2) Urban Freeways, and 3) Arterials and Collectors. Based on the available information from the three groups, the condition states were defined as presented in Table 7.

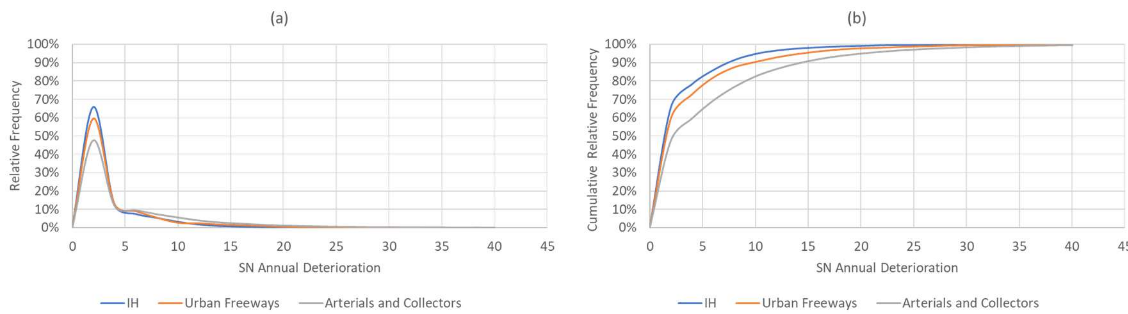

Figure 16: SN Deterioration Rates presented as a a) Distribution of SN Annual Deterioration, and b) Cumulative SN Annual Deterioration.

Table 7: Condition States Defined for the Case Study

Condition State	Lower SN Bound	Upper SN Bound	Crash Rate per Million VMT
1	51	100	0.866
2	41	50	0.861
3	31	40	1.022
4	21	30	1.135
5	1	20	1.498

The transition probability matrix (***P***) was estimated as outlined in the Methodology. The matrix ***P*** was cross-validated and the p-values for the three groups were 0.891, 0.948, and 0.905 respectively, thus validating the deterioration models. Table 8 presents the matrix ***P*** obtained for the three groups after validation.

Table 8: Deterioration Transition Probability Matrix (Matrix ***P***) of the MC Model

Matrix ***P*** for Interstate Highways					
Condition State	1	2	3	4	5
1	0.768	0.232	0.000	0.000	0.000
2	0.000	0.494	0.506	0.000	0.000
3	0.000	0.000	0.758	0.201	0.040
4	0.000	0.000	0.000	0.879	0.121
5	0.000	0.000	0.000	0.000	1.000
Matrix ***P*** for Urban Highways					
Condition State	1	2	3	4	5
1	0.273	0.727	0.000	0.000	0.000
2	0.000	0.096	0.904	0.000	0.000
3	0.000	0.000	0.444	0.129	0.427
4	0.000	0.000	0.000	0.950	0.050
5	0.000	0.000	0.000	0.000	1.000
Matrix ***P*** for Arterials and Collectors					
Condition State	1	2	3	4	5
1	0.702	0.298	0.000	0.000	0.000
2	0.000	0.216	0.340	0.445	0.000
3	0.000	0.000	0.757	0.043	0.199
4	0.000	0.000	0.000	0.832	0.168
5	0.000	0.000	0.000	0.000	1.000

Estimating the Lane Miles to Be Treated per Year

The matrix ***M*** is developed with two considerations: *a*) the type of treatment to improve SN that is selected for the analysis, and *b*) the new SN value after the treatment is applied. This study performs the analysis for seal coats, which is a type of treatment commonly used in the Austin District and TxDOT Highways for preventive maintenance purposes. Likewise, some seal coats are applied to improve of the SN of the pavement as a means to reduce wet-weather crashes (TxDOT, 2017). Seal coats consist of the application of a thin layer of asphalt material covered with a single layer of aggregate. The asphalt layer functions as a seal of the cracks of the underlying pavement and binds the aggregates, while the aggregates transfer the load to the underlying pavement and provide friction. Though different asphalt material and aggregates can be used, seal coats are relatively inexpensive and for this reason they have been used as a treatment to reduce wet-weather crashes (TxDOT, 2017). It has been observed that seal coats have an average service life of 6 years, with some of them lasting up to 20 years (TxDOT, 2017).

Once applied, seal coats usually improve the SN values to the range between the upper fifties and low forties (Chowdhury, Kassem, Aldagari, & Masad, 2017; Pratt, et al., 2014). Therefore, in the matrix $\boldsymbol{M}$, sections treated will improve the SN condition from their initial condition state to 50 percent in condition state 1 and 50 percent in condition state 2.

For the unit cost of the seal coat, a set of TxDOT winning bids from the months of January, March and April of 2015 were analyzed. The information on a total of 181 projects was collected from the "Letting Schedule" and "Plans Online" portals of TxDOT (TxDOT, 2015; TxDOT, 2015b). The scopes and details of the projects were examined, and a total of 23 seal coat projects were identified. The costs per lane mile of the seal coat projects presented high variability, with costs ranging between \$8,000 and \$71,000. The median cost per lane mile was \$17,000 in 2014 USD. These costs included the transportation and mobilization of equipment to the treatment location, traffic control, labor, materials, and additional items required to complete the project. With the purpose of evaluating the sensitivity of the BCR to the seal coat cost, three costs per lane mile are used: *a*) the 25th percentile cost (\$13,000), *b*) the median cost (\$17,000), and *c*) the 75th percentile cost (\$24,000). These values represent a low cost, median cost, and high cost scenario respectively.

The travel time delay was estimated as the additional time to cross the work zone with a speed reduction of 20 mph from the posted speed. The results of the delay and depreciation costs for each functional system group are presented in Table 9. The safety costs were estimated using a CMF of 1.77 that is applicable for lane closure of highways and for all types of crashes (Ullman, Finley, Bryden, Srinivasan, & Council, 2008). This CMF can be accessible in the CMF clearinghouse database of FHWA.

Table 9: Total Delay and Depreciation Costs per Vehicle Per Section Treated

Functional System Group	Total Delay and Depreciation Costs per Passenger Car ($2014)	Total Delay and Depreciation Costs per Single-Unit Truck ($2014)	Total Delay and Depreciation Costs per Combination Truck ($2014)
1	$0.22	$0.18	$0.26
2	$0.20	$0.22	$0.32
3	$0.20	$0.22	$0.32

Estimate Crash Reduction Benefits

Information from the Crash Record Information System (CRIS) was merged with the SN dataset for the years from 2010 to 2015. A total of 8,370 crashes were located in sections with known SN. Using this information, the crash rates per million VMT were estimated for each condition state as shown in Table 7 and Figure 17.

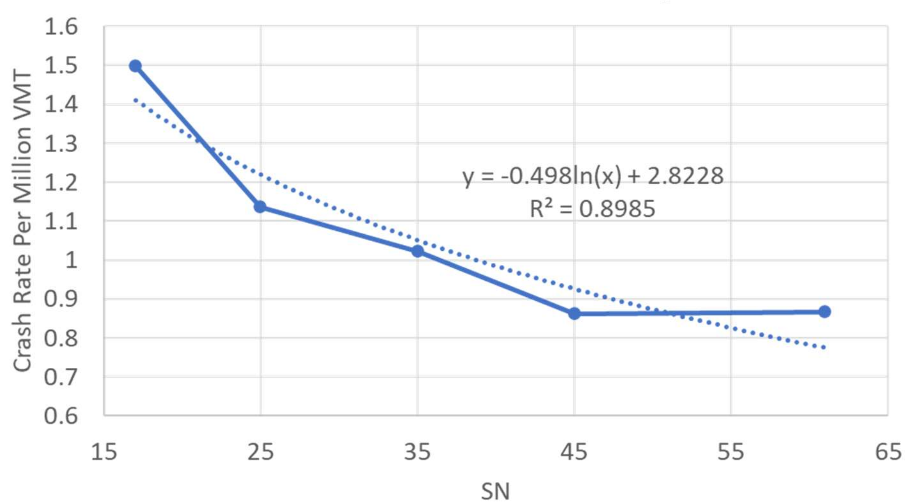

Figure 17: Crash Rates per Million VMT as a Function of Skid Number for the Sample Network

The average cost per crash was estimated using: a) the distribution of crash severity in the state of Texas in 2012 (TxDOT, 2019b), and b) the respective crash severity cost used for safety analysis with the most recent update by the U.S. DOT "Benefit-Cost Analysis Guidance for Discretionary Grant Programs" (2020). The Average Cost per Crash is presented in Table 10.

Table 10: Distribution of Crash Severity in Texas in 2012 and Their Respective Costs for Safety Analysis

KABCO LEVEL	Monetized Value ($2018)	Monetized Value ($2014)	Number of People (for "Unknown if Injured" is the Number of Accidents)	Cost by Severity ($2014)
O - No Injury	$ 3,200	$ 3,004	46,584	$ 139,918,153
C - Possible Injury	$ 63,900	$ 59,977	8,832	$ 529,721,044
B - Non-Incapaciting Injury	$ 125,000	$ 117,327	7,175	$ 841,819,974
A - Incapaciting	$ 459,100	$ 430,918	1,311	$ 564,933,452
K - Killed	$ 9,600,000	$ 9,010,700	215	$ 1,937,300,544
U - Injured (Severity Unknown)	$ 174,000	$ 163,319	3,096	$ 505,635,442
# Accidents Reported (Unknown if Injured)	$ 132,200	$ 124,085	942	$ 116,887,929
			Total	**$ 4,636,216,538**
			Number of Crashes in 2012	**25,068**
			Cost Per Crash ($2014)	**$ 185,000**

BCR Results

The service life of the treatments was estimated as outlined in the Methodology. The skid resistance deterioration model of each Functional System group was used and the worst condition state (condition state 5) was defined as the failing state. The resulting analysis period is 13 years for Interstate Highways, 4 years for Urban Freeways, and 7 years for Arterials and Collectors.

The BCR was estimated for the respective life service of the treatment for the three seal coat cost scenarios defined: *a*) a low-cost scenario using the 25th percentile cost ($13,000 per lane mile), *b*) a median cost scenario using the median cost ($17,000 per lane mile), and *c*) a high-cost scenario using the 75th percentile cost ($24,000 per lane mile). Figure 18 presents the results for the three functional system groups analyzed for comparison purposes while Figure 19, Figure 20 and Figure 21 presents the results separately for Interstate Highways, Urban Freeways and Arterials and Collectors respectively.

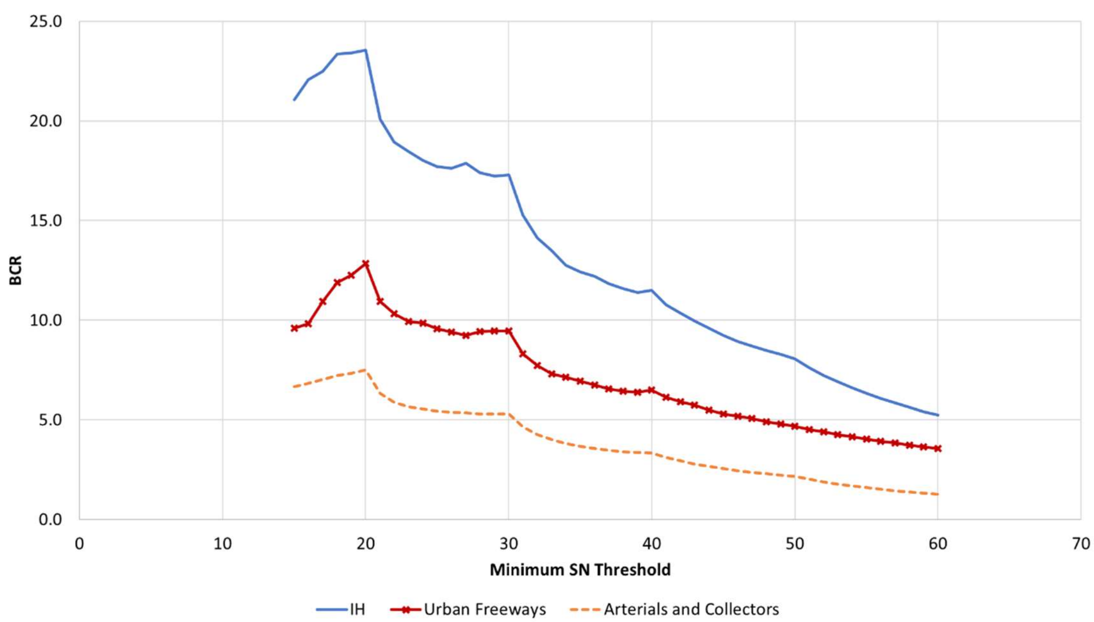

Figure 18: Benefit-Cost Ratio of Establishing a Minimum SN Threshold for Interstate Highways, Urban Freeways and Arterials and Collectors, Using the Median Cost

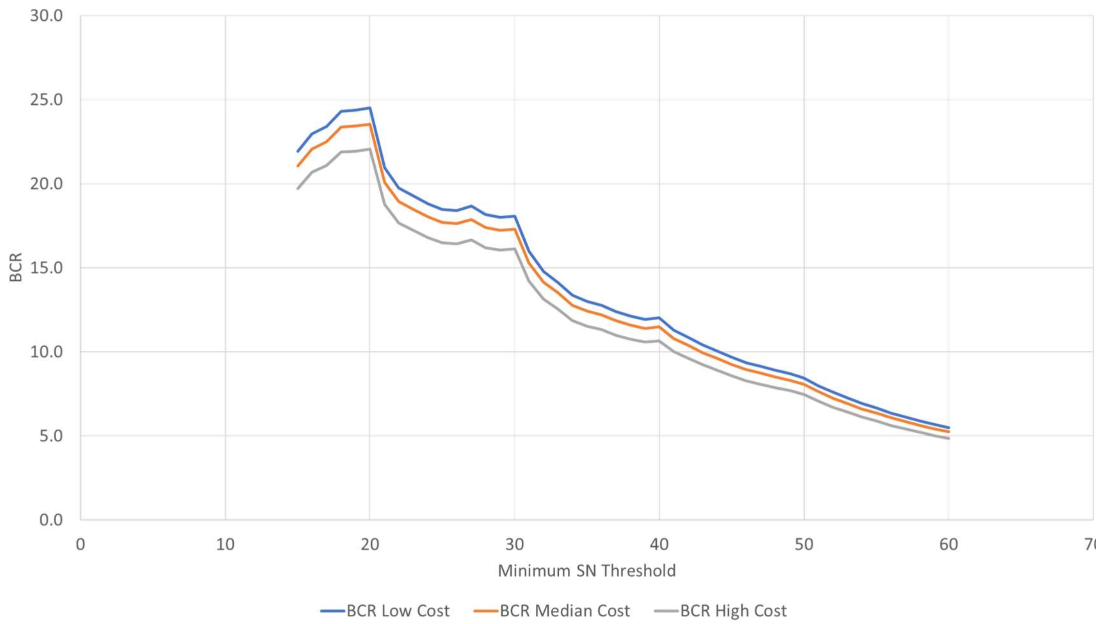

Figure 19: Benefit-Cost Ratio of Establishing a Minimum SN Threshold for Interstate Highways

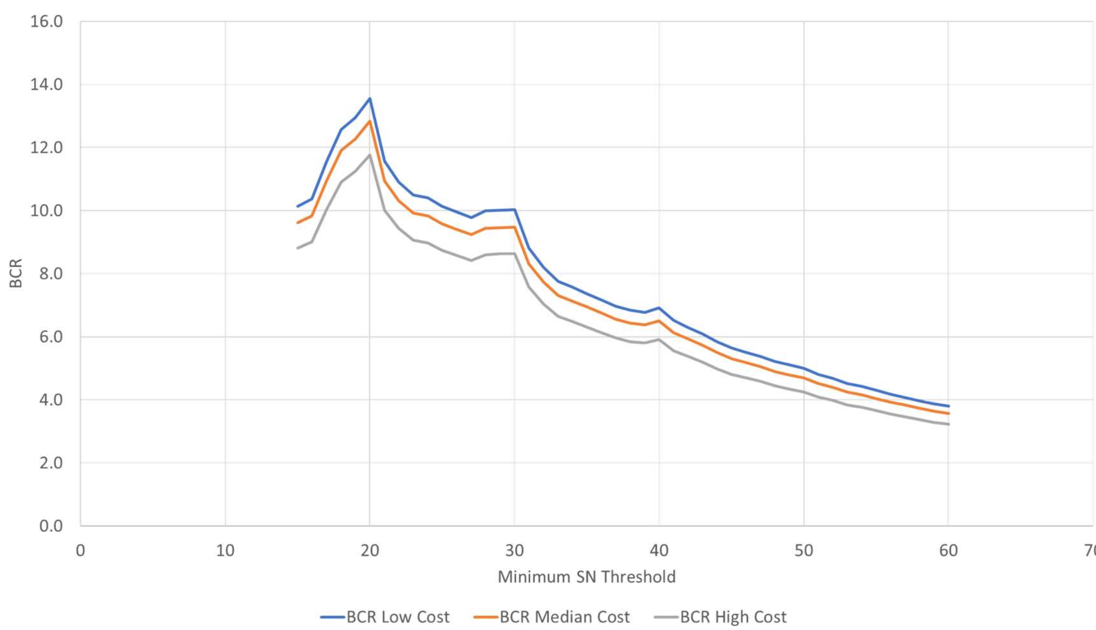

Figure 20: Benefit-Cost Ratio of Establishing a Minimum SN Threshold for Urban Freeways

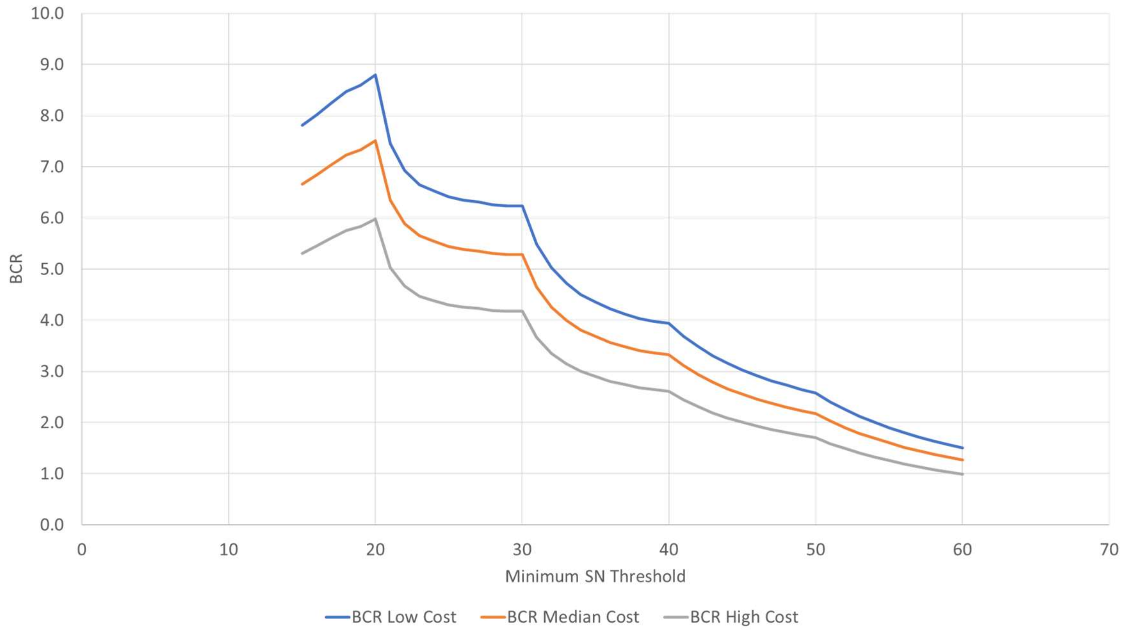

Figure 21: Benefit-Cost Ratio of Establishing a Minimum SN Threshold for Arterials and Collectors

The results show that the BCR has a relatively small variability as a consequence of the variability of the seal coat costs. For example, for Interstate Highways, a minimum SN threshold of SN=20 the BCR ranges between 24.5 and 22.0. The variability is even smaller for Urban Freeways and Arterials and Collectors.

For all scenarios, the BCR is greater than 1.0, indicating the potential economic benefits of establishing a minimum SN threshold for the roadway network. The BCR is higher for Interstate Highways and lower for Arterials and Collectors, which is consistent with what previous researchers have found about the importance of higher SN thresholds for high traffic highways (Kuttesch, 2004; Wu, Zhang, Long, & Murphy, 2014).

The general BCR trends have a negative slope meaning that lower SN intervention thresholds will yield a higher BCR. When a low friction pavement is treated, a higher crash reduction per lane mile treated is expected. These results mean that increasing the minimum SN threshold increases the maintenance costs at a higher rate than the increase of the benefits (total crash reductions). However, it is important to highlight that a decreasing BCR does not mean that treating the worst pavements first is the best maintenance strategy. The scope of the paper is to estimate the BCR when an agency is applying the intervention threshold strategy. Therefore, the results should be understood as if an agency is applying the intervention threshold strategy, these are BCR results expected. In that case, transportation agencies need to balance between establishing a) a low SN intervention threshold with higher BCR, but lower expected total crash reductions; or b) a high SN intervention threshold with higher expected total crash reductions, but lower BCR.

The order of magnitude of the BCRs obtained is similar to those estimated by Brimley and Carlson (2012) (BCR ranging from 60 to 20 over a 5-year period for horizontal curves), Long et al. (2014) (BCR ranging from 39.6 to 20.0 over a 4-year period for a whole network when the minimum SN is 28), and the average before-and-after BCR found by Wilson et al. (2016) (average BCR of 24.5 over a 5-year period for HFSTs applied on tight curves).

Another metric that can be estimated is the average BCR of improving the SN of a section from a given initial value, using seal coats as a treatment. This metric is different from the minimum SN threshold BCR because it does not consider treating the pavement sections with a SN below the threshold. For example, for SN=20, it means that all the sections with SN=20 are treated, while the sections with SN below or above 20 are not treated. This metric is estimated using the benefits and costs for a given SN threshold, then subtracting the cumulative benefits and costs of treating sections with SN lower than the SN threshold, and then estimating the BCR. The results using the middle point of the condition states are presented in Figure 22 and Table 11. The middle points are used because of the discontinuity caused when the SN was grouped in condition states. Figure

22 shows a decreasing trend that has a maximum of 29.5 for SN=17 for Interstate Highways, and reaches values below 1.0 around SN 40 for Urban Freeways and Arterials and Collectors. The values close to zero reflect the fact that pavements with an initial SN that is high will not experience further crash reductions (and, thus, no benefits) due to seal coats.

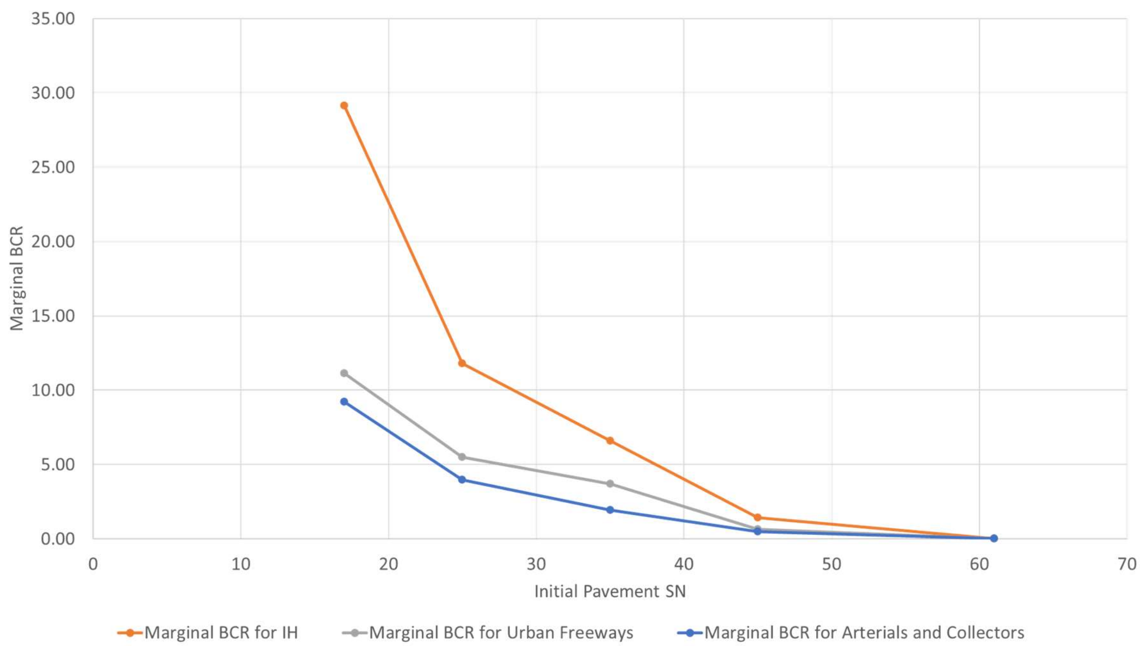

Figure 22: Average Benefit-Cost Ratio of Improving the SN Using Seal Coats For 1) Interstate Highways, 2) Urban Freeways, 3) Collectors and Arterials

Table 11: Average Benefit-Cost Ratio of Improving the SN Using Seal Coats For 1) Interstate Highways, 2) Urban Freeways, 3) Collectors and Arterials.

Condition State	Marginal BCR IH	Marginal BCR Urban Freeways	Marginal BCR Arterials and Collectors
5	29.15	11.12	9.23
4	11.78	5.48	3.98
3	6.60	3.69	1.94
2	1.41	0.63	0.48
1	0.00	0.00	0.00

It is important to highlight that this estimation is the potential economic-benefits of applying safety-only treatments. However, SN can be improved due to other pavement preservation activities as well. If this data is available, it could be estimated the economic benefits of pavement preservation and crash reduction of regular pavement preservation activities.

3.3 Conclusions

In this study, a framework for estimating the BCR of establishing a SN intervention threshold was proposed. In the proposed methodology, a MC deterioration model was employed to quantify the number of lane miles to be treated, which, in turn, yields the maintenance cost for the network. Other indirect costs included were the travel time delay costs and the safety costs due to the presence of work zones. The crash rates per VMT were used to estimate the crash reductions, which were then converted to monetary value to represent the benefit. The conclusions of the study are summarized as follows:

1. The most important contribution of this paper is to provide a methodology that transportation agencies can use as an analytical tool to estimate the BCR of maintenance policies that intended to provide a minimum SN in a roadway network. This estimation is designed to be replicable in different contexts, which contrasts

to previous studies where either the treatment cost or the benefit of crash reduction was based on engineer's judgement, assumptions or local experience. Although the case study used data specific to seal coats from the Austin District, the methodology can be applicable to different treatments and different networks. The two key elements that are needed are a MC deterioration model and a function that links crash rates with pavement friction. Moreover, this analysis is not limited to Skid Number but can be applied to SFC measurements as well. For instance, a deterioration model similar to the one developed by Fulop (2000) for SFC can be used to estimate the treatment needs, and a model similar to Davies et al. (2005) where crash rates per 100 million Vehicle-Kilometer are a function of SFC can be used to estimate the crash rates in each condition state. Furthermore, economic variables for inclusion in the analysis can be adjusted to local conditions as well.

2. The developed framework allows to incorporate travel delay costs and safety costs due to the presence of work zones, making the BCR more comprehensive. With this consideration, the costs due to traffic disruptions can also be taken into the BCR analysis.
3. The scope of the paper was to estimate the BCR when an agency is applying the intervention threshold strategy, but this paper did not assess if this is the best maintenance strategy. Therefore, the results should be understood as if an agency is applying the intervention threshold strategy, these are BCR results expected. Further research is needed to estimate the cost-effectiveness of different maintenance strategies in order to compare different policies aiming to manage skid resistance at the network level.

Chapter 4: Incorporating Skid Number into the Pavement Management Process

In chapter 2, the feasibility of using Markov Chains for modeling skid resistance deterioration was tested. In particular, future condition of Skid Number (collected using the ASTM E274/E274M-15) was predicted using the proposed framework within the acceptable ranges. In chapter 3, the methodology to quantify the Benefit-Cost Ratio of establishing a SN intervention threshold at the network level was developed. This Benefit-Cost Ratio included the maintenance costs, the monetary value of delays for road users due to maintenance, the monetary value of road safety risk due to the work zones, and the monetary benefits of crash reduction.

In this chapter, three alternatives to incorporate Skid Number into the pavement management process are proposed. This includes an overview of the pavement management plans and the framework for budget planning and budget allocation. A case study with 200 highway pavement sections from Texas was used to demonstrate the applicability of the three alternatives propose. The chapter concludes with the major findings of the study.

This chapter is part of a paper draft that is expected to be submitted for journal publication by Summer 2021.

4.1 BACKGROUND

Highways are a critical component of the transportation system and the economy. The adequate maintenance of highways is crucial to keep the movement of people and goods. Furthermore, there is a global trend of increasing pressure for safer roads and for adopting a “zero fatalities” vision. This global trend translates into higher expectations from the public of not only highways in good condition but also highways that are safe to use.

This section explores the importance of the highway system for Texas, an overview of the current budget planning and budget allocation problem, and a summary of the current PMP process in Texas. The section concludes with an overview of the Condition Score index.

Complexity of Texas Highways

Texas is the 2nd largest economy in the United States, and the 10th largest economy in the world. It is estimated that more than 2 billion tons of freight move through the state, with more than a half being moved on the highway system (TxDOT, 2020). Texas also is the 2nd most populous state in United States with 28 million people.

Texas economy and population continue growing. It is expected that by 2045 the freight movement will double and that the population will reach 39 million (TxDOT, 2020). This growth poses a pressure to expand the system and to preserve current assets to satisfy future demand. However, historically, the network has expanded at a slower pace than the increasing demand of the highways. For example, from 1990 to 2013, Daily VMT increased 70 percent and Truck Daily VMT 110 percent, while centerline miles increased only 7 percent (Figure 23) (TxDOT, 2020). Therefore, there is a greater pressure on preserving existing highway assets instead of expanding them.

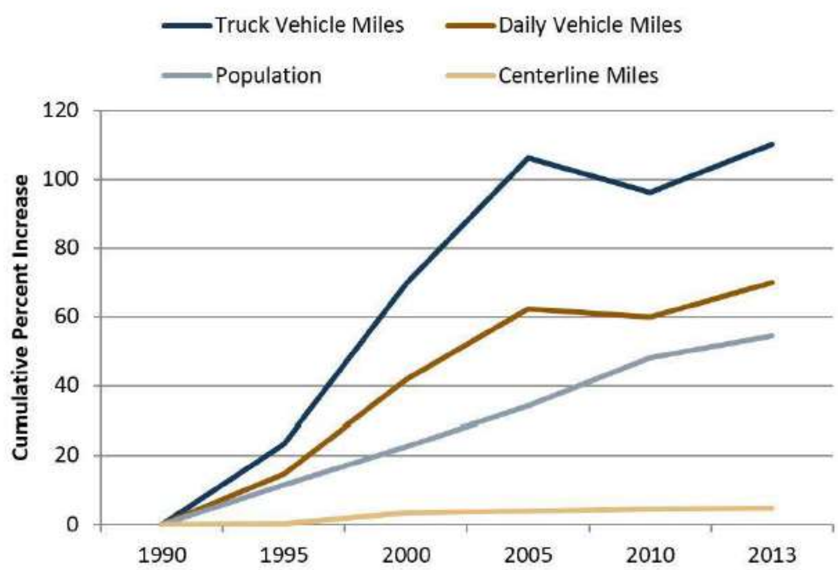

Figure 23: Historical Growth Trend of Daily VMT, Truck Daily VMT, Population and Centerline Miles (TxDOT, 2020)

The extension of the highway system and the geographic heterogeneity of Texas make the management of pavements a challenging task. The Texas Department of Transportation (TxDOT) manages both the largest and busiest highway network in the United States. The On-System includes around 190,000 lane-miles, with 61,219 of them being designated as part of the National Highway System (NHS) (TxDOT, 2020).

Texas highways are composed by three types of pavements: Asphalt Flexible Pavement (ACP), Continuous Reinforced Concrete Pavement (CRCP), and Jointed Concrete Pavement (JCP), all of them with different deterioration rates and properties. Furthermore, the geographic heterogeneity of Texas adds a complexity to manage the pavements because of the combination different subgrade types and climates, as can be seen in Figure 24 (TxDOT, 2018):

- Zone 1 covers wet-cold climate and poor, very poor, or mixed subgrade.
- Zone 2 covers wet-warm climate and poor, very poor, or mixed subgrade

- Zone 3 covers dry-cold climate and good, very good, or mixed subgrade
- Zone 4 covers dry-warm climate and good, very good, or mixed subgrade

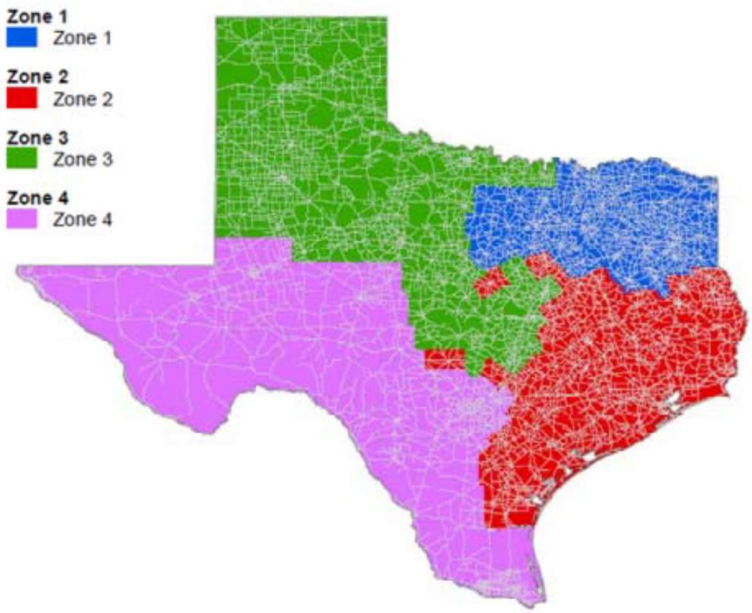

Figure 24: Zone Classification of Climate and Subgrades for Pavement Deterioration Models (TxDOT, 2018)

Two of the goals of TxDOT (Preserve our Assets, and Promote Safety) are aligned with the overall objectives of preserving highway assets in good condition and provide a safer infrastructure (TxDOT, 2020b). However, declining funding from traditional sources, such as the decreasing purchasing power of the state and federal gas tax, call for more efficient use of available resources (TxDOT, 2021). In this context, multiple transportation agencies have faced the challenge of allocating the available budget in the most efficient way attending multiple goals at the same time (Wiegmann & Yelchuru, 2012; Spy Pond Partners, High Street Consulting Group, Burns & McDonnell, 2019). This challenge of allocating limited resources can be systematically addressed solving two distinct but related problems: budget planning and budget allocation. The following section presents an overview of these two problems.

Budget Planning and Budget Allocation

Since the 1970, transportation agencies have design systems to manage their pavement infrastructure. These early pavement management systems evolved over time from monitoring-only systems to more proper management systems by 1990s. Since the 2000s, as new technological resources became available, new tools and new procedures for data collection were implemented, resulting in the modern pavement management systems currently used by transportation agencies.

Highway agencies manage their pavements at two levels: project level and network level (Uddin, Hudson, & Haas, 2013). At the project level, agencies focus on defining the best Maintenance and Rehabilitation (M&R) strategy for a given project. Therefore, at the project level the analysis is site-specific. In contrast, at the network level the focus are the policies and budget planning for the whole network, thus comprising a group of pavement sections. This paper focuses on network-level analysis.

There are two important problems for pavement management at the network level: budget planning and budget allocation (Zhang, 1996; Uddin, Hudson, & Haas, 2013). Both problems involve an optimization, although the objective and constraints of each problem is different. Budget planning is the process of defining the M&R program that would yield the minimum budget necessary to achieve a set of goals under given constraints. In contrast, budget allocation is the process of defining the M&R program that would yield the maximum performance of the network for a fixed budget under given constraints. In summary, budget planning is used to estimate the minimum budget needed, and budget allocation is used to maximize the performance of a network for a fixed budget.

Although different transportation agencies use different steps and components in their budget planning and budget allocation, the general process can be summarized as it is shown in Figure 25 (Spy Pond Partners, High Street Consulting Group, Burns & McDonnell, 2019). The process starts with two sets of inputs: Strategic Decisions and Goals (such as the performance metric and the target for the performance metric) and the Network-Level Asset Data (such as the asset inventory and the average deterioration rates). These two sets are the input for the Budget Planning problem, where the minimum budget needed to achieve the targets is estimated. Afterwards, if the budget needed is greater than the available funding, the Budget Allocation problem is solved. The objective of the Budget Allocation is to maximize the performance of the network for the available budget. If the expected performance is not acceptable, the stakeholders can increase the available funding or change the strategic decisions and goals. In that way, the whole process may require multiple iterations until the expected performance is acceptable to the stakeholders.

Multiple transportation agencies develop a Pavement Management Plan (PMP) in order to solve the Budget Planning and Budget Allocation problems. In short, PMPs are a systematic way of allocating resources to maximize the performance of the network. The following section presents an overview of the PMP developed for Texas.

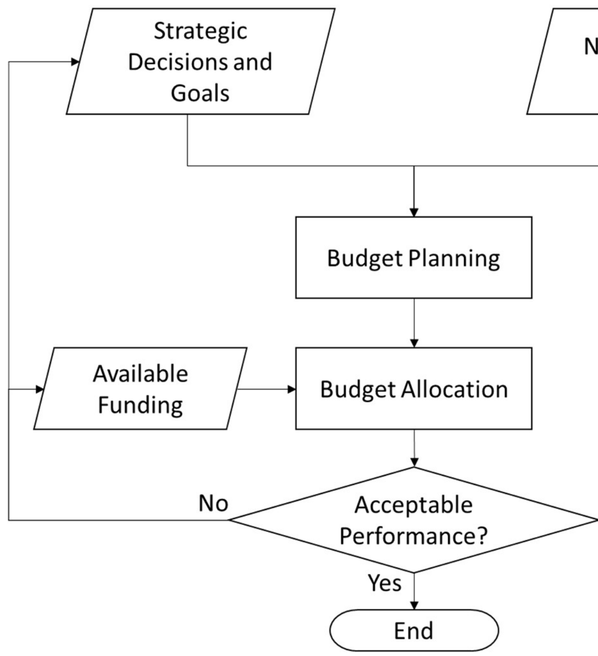

Figure 25: High-Level Overview of the Budget Planning and Budget Allocation Process

Overview of the Pavement Management Plan in Texas

TxDOT develops a 4-Year PMP where districts identify pavement preservation needs (Budget Planning), projects to be prioritized (Budget Allocation), and estimate the expected performance as a result of the proposed projects. TxDOT used the results of each District to prepare a single PMP report every four years that summarize the results. The most recent version covers Fiscal Years 2019 through 2022 (TxDOT, 2018).

The development of the PMP is not only a technical tool but also a legal requirement. After the Rider 55 appropriations bill was approved by the State Legislature, TxDOT needs to provide the Governor and the Legislative Budget Board a detailed plan of the investments and a district-by-district summary of the pavement scores achieved. This requirement must be fulfilled at the beginning of each Fiscal Year. In particular, the most recent 4-Year PMP highlights that the objectives of the document are more comprehensive than only identifying the projects needed (TxDOT, 2018):

- "Develop a comprehensive and uniform pavement management plan which is roadway specific to the greatest extent possible, and is fiscally constrained.
- Generate Pavement Condition Projections based on a financially constrained plan.
- Assure maintenance resources are directed towards pavement operations and roadway related work.
- Provide a reporting mechanism for District Engineers, Administration and Commission to utilize in briefing elected officials.
- Allow districts and regions to appropriately allocate resources through long term planning in order to accomplish the plan." (TxDOT, 2018, p. 7)

TxDOT groups the different pavement treatments into four levels: Preventive Maintenance (PM), Light Rehabilitation (LR), Medium Rehabilitation (MR) and Heavy Rehabilitation (HR). The summary of the treatments included in each level is presented in Table 12 (TxDOT, 2018).

TxDOT uses the software Pavement Analyst™ (PA) to store the condition of the pavement sections and to solve the Budget Allocation optimization using linear-programming based algorithms (TxDOT, 2018). The results are the number of lane-miles that are planned to receive either PM, LR, MR or HR. Figure 26 presents the summary of lane-miles planned for treatment during FY19-FY22.

Table 12: Summary of the Treatments Included In Each Treatment Level (TxDOT, 2018)

Treatment Level	Treatments Included
Preventive Maintenance (PM)	• Seal coat • Thin overlay 2 inches thick or less • Mill and inlay 2 inches or less • Hot in-place recycling • Micro-surfacing or slurry seal • Scrub seal
Light Rehabilitation (LR)	• Overlay greater than 2 inches thick but no more than 4 inches • Mill and inlay greater than 2 inches thick but no more than 4 inches
Medium Rehabilitation (MR)	• Overlay greater than 4 inches but no more than 6 inches • Mill and inlay greater than 4 inches but no more than 6 inches • White-topping
Heavy Rehabilitation (HR)	• Overlay greater than 6 inches • Mill and inlay greater than 6 inches • Full reconstruction • Full depth reclamation (pulverization and stabilization) with new hot-mix asphalt surface • Full depth reclamation (pulverization and add new base) with new seal coat surface

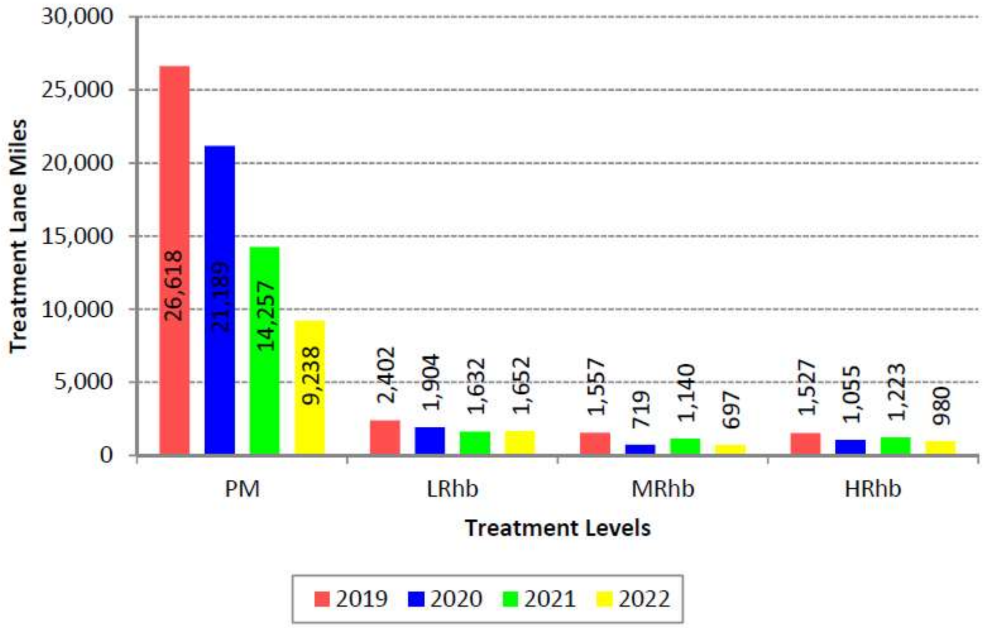

Figure 26: Summary of Lane-Miles to be Treated During FY19-FY22

The Texas Transportation Commission has set the target of "90 percent of the pavements to be rated Good or better condition." In order to assess if a pavement is in "Good or better condition," TxDOT rates the pavements every year using an index called Condition Score. This index is a key component of the PMP process. The following section presents an overview of the Condition Score.

Overview of the Condition Score

The Condition Score (CS) is a composite score that aims to capture the condition of the pavement. The CS ranges from 1 (worse score) to 100 (best score). The pavements are rated as either in Very Good, Good, Fair, Poor, and Very Poor condition depending on the value of CS, as it is shown in Table 13 and Figure 27.

Table 13: Pavement Condition as a Function of the Condition Score (Goehl, 2014)

Condition Score Range	**Condition**
$CS \geq 90$	Very Good
$70 \leq CS < 90$	Good
$50 \leq CS < 70$	Fair
$35 \leq CS < 50$	Poor
$1 \leq CS < 35$	Very Poor

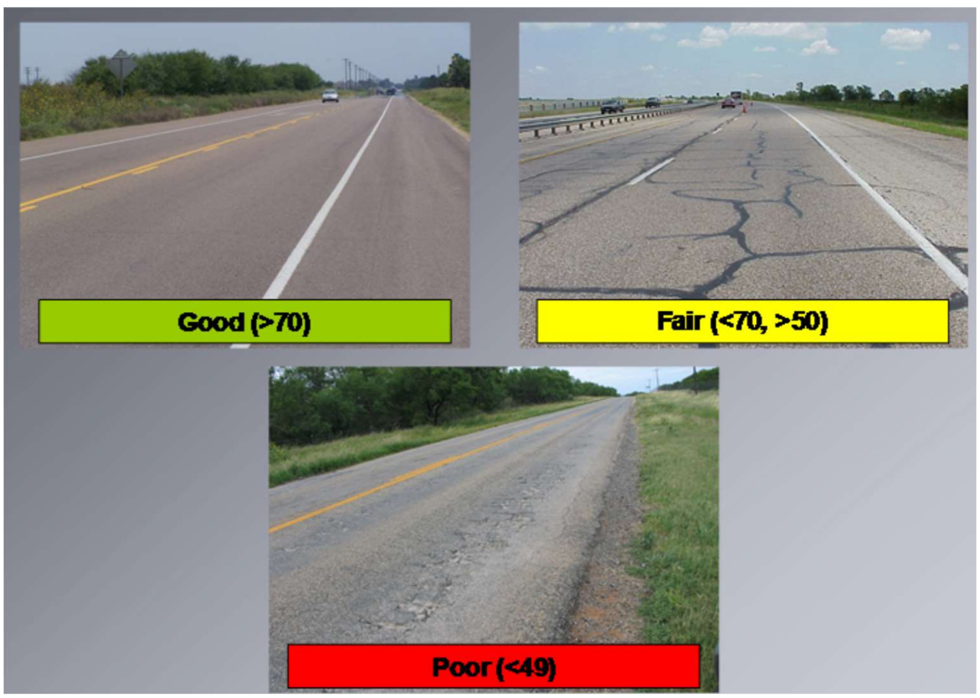

Figure 27: Visual Pavement Condition of Different Condition Scores (TxDOT, 2018)

The CS is composed of two others indices: the Distress Score (DS) and the utility value of the Ride Score, as can be seen in Equation 20.

$$CS = DS * U_{Ride} \tag{20}$$

Where,

CS = Condition Score

DS = Distress Score

U_{Ride} = Utility value for the Ride Score

The DS is itself a composite index of multiple utility functions corresponding to individual distress types. For each pavement section, the density of individual distress types (L_i) is collected according to their specific unit (for example, quantity of distresses per section or area affected). For ACP, the distresses are Shallow Rutting, Deep Rutting, Patching, Failures, Alligator Cracking, Block Cracking, Longitudinal Cracking, and Transverse Cracking (Figure 28). The individual distress densities (L_i) are transformed using utility functions. The generic equation and shape of these utility functions are presented in Equation 21 and Figure 29.

Figure 28: Visual Examples of Distresses for ACP (Goehl, 2014)

$$U_i = \begin{Bmatrix} 1.0, & L_i = 0 \\ 1 - \alpha * e^{-\left(\frac{\rho}{L_i}\right)^{\beta}}, & L_i > 0 \end{Bmatrix} \tag{21}$$

Where,

U_i = Utility value of distress density L_i

L_i = Distress density of distress i

α = Parameter that controls the maximum loss

ρ = Parameter that controls the elongation of the point of inflection

β = Parameter that controls the slope

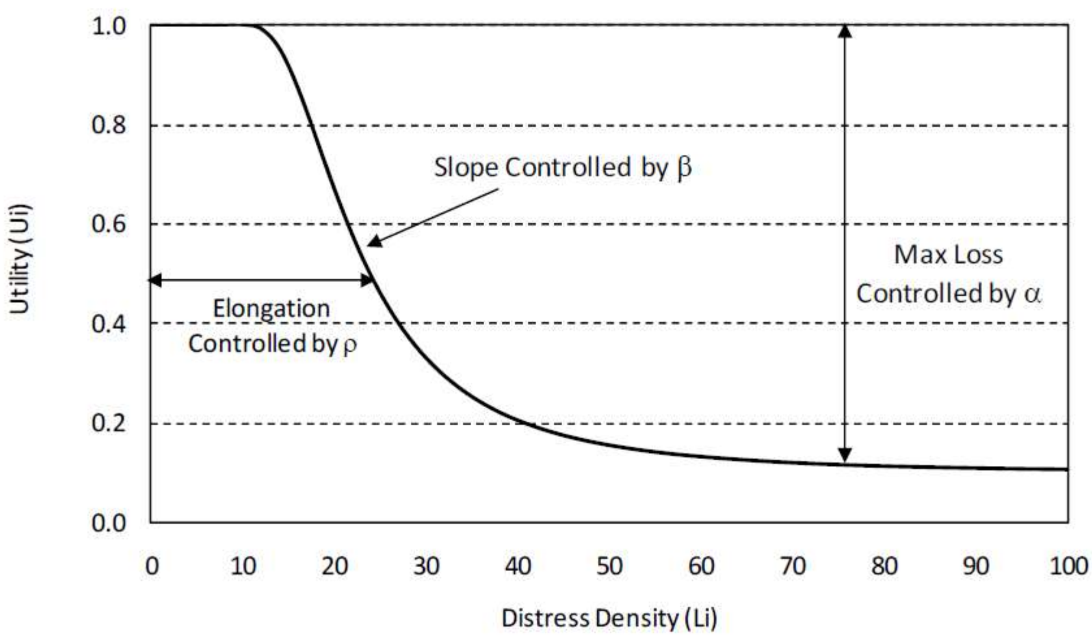

Figure 29: Generic Shape and Parameters of the Utility Functions (Gharaibeh, et al., 2012)

The utility functions U_i represent the usefulness of the pavement in the presence of distress densities L_i. The utility functions can range from 1.0 (no impact) to zero (the pavement is no longer useful). Once the utility values are estimated for all the distress densities, the Distress Score is estimated as the product of all the utility values, as shown in Equation 22.

$$\begin{aligned} DS &= 100 * \prod U_i \\ &= 100 * U_{SRut} * U_{DRut} * U_{Patch} * U_{Fail} * U_{Allig} \\ &\qquad * U_{Blk} * U_{Lng} * U_{Trn} \end{aligned} \tag{22}$$

Where,

DS = Distress Score

U_{SRut} = Utility value for Shallow Rutting

U_{DRut} = Utility value for Deep Rutting

U_{Patc} = Utility value for Patching

U_{Fail} = Utility value for Failures

U_{Allig} = Utility value for Alligator Cracking

U_{Blk} = Utility value for Block Cracking

U_{Lng} = Utility value for Longitudinal Cracking

U_{Trn} = Utility value for Transverse Cracking

The Ride Score (the second component of the Condition Score) is measured according to the International Roughness Index (IRI) on both wheel paths at highway speed. The units of the IRI are inches/mile, and it can range from 0 (best condition) to +950 (worst condition). The IRI value is then transformed using a utility function similar to the ones shown in Equation 21 and Figure 29.

Once the CS is estimated as the product of DS and the utility value of the Ride Score, this index becomes the key parameter of the Pavement Management Plans. The CS is used to rate the condition of the network and measure the performance as the percentage of pavements in Good or better condition. Moreover, the objective function of the Budget Allocation is the maximization of the CS performance of the network. As a consequence, the PMP process relies heavily on the CS.

Research Objectives

Although the CS includes pavement distresses and the ride quality, it does not include pavement friction. As presented in chapters 1-3, pavement friction (and in particular, Skid Number (SN)) is an important pavement factor that is related to road crashes, and its incorporation into the PMP process can be aligned with TxDOT's goal of providing safer highways. This contrast with other agencies such as the New Zeeland's Transportation Agency that started to incorporate skid resistance into the pavement preservation analysis (OPUS, 2016). Therefore, the objective of this chapter is to provide a framework to incorporate SN into the PMP process. In particular, this chapter proposes three alternatives to incorporate SN into the PMP process:

1. Include a Constraint that Limits the Decline of SN Performance Over Time
2. Create a New Overall Performance Function that incorporates CS and SN
3. Redefine CS as CS* to Incorporate SN

This chapter is organized as follows. The methodological framework for the PMP process is presented. Then, an explanation of the steps involved in this framework is presented. Subsequently, to demonstrate the applicability of the three alternatives, a case study is conducted to a sample of pavement sections of the Austin District. Finally, the results and conclusions of this study are presented.

4.2 METHODOLOGICAL FRAMEWORK

The methodological framework comprises four components: (a) the definition of the strategic decisions and goals, (b) the collection of network-level asset data, (c) the optimization process, and (d) the estimation of road crashes and other costs. The framework is depicted in Figure 30.

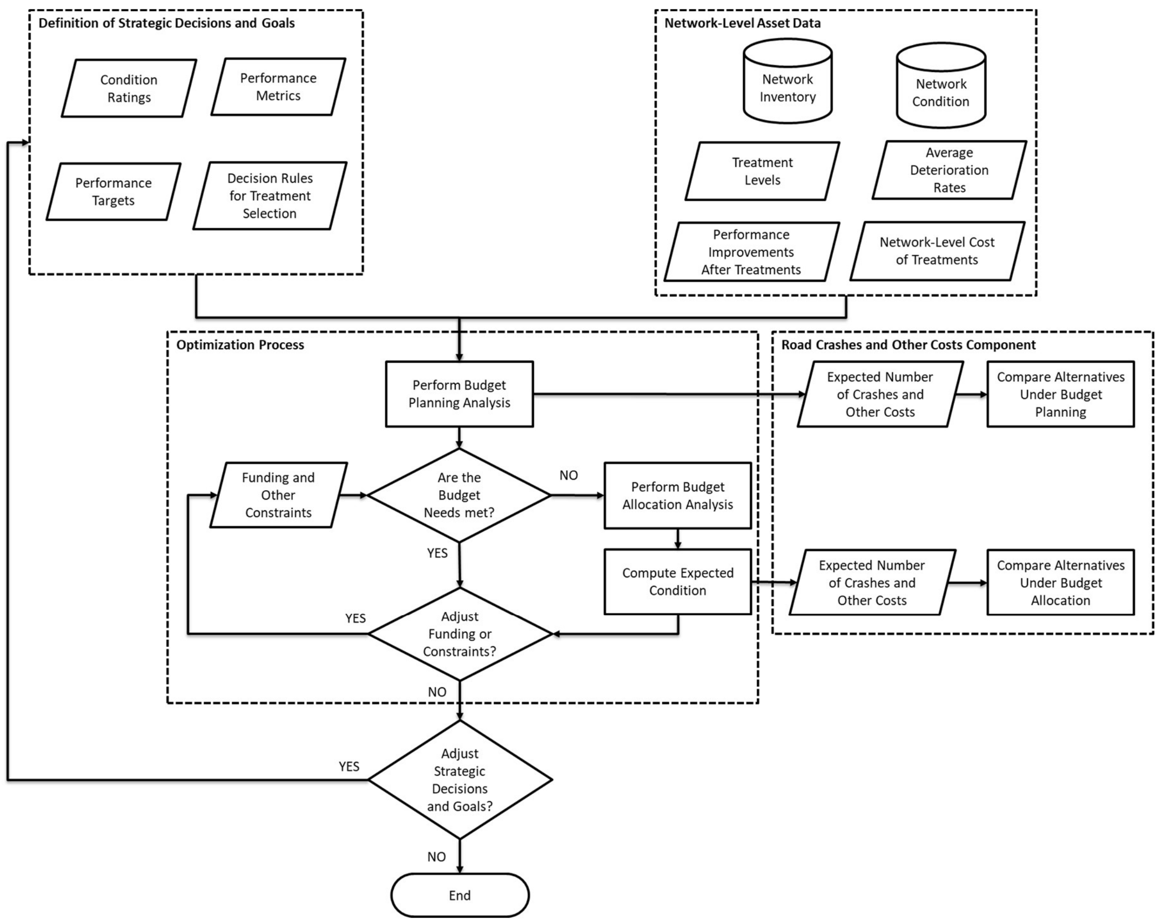

Figure 30: Methodological Framework to Incorporate SN into the Pavement Management Process

Definition of the Base Scenario and Alternatives Proposed

This framework proposes three alternatives to incorporate SN into the PMP process. An additional base scenario where SN is not incorporated into the PMP process is included for comparison. Table 14 summarizes the alternatives proposed.

It is important to highlight that the Budget Planning and Budget Allocation processes are solving different problems. Therefore, these alternatives will have different objective functions and constraints depending if the problem being solved is Budget Planning or Budget Allocation. The section “Optimization Process” provides a detailed explanation of the objective functions and constraints for each alternative under Budget Planning and Budget Allocation problems.

Table 14: Base Scenario and Alternatives Proposed to Incorporate SN Into the PMP Process

Alternative	Description
Base Scenario	Perform the current practice where SN is not considered in the PMP process
Alternative 1	Include a constraint that limits the decline of SN performance over time
Alternative 2	Create a New Overall Performance Function that incorporates CS and SN
Alternative 3	Redefine CS as CS* to incorporate SN

Base Scenario: Considering CS Only

This scenario is the current process performed by TxDOT to develop the PMP. In this scenario, only CS is considered during the PMP process.

Alternative 1: Include a Constraint that Limits the Decline of SN Performance Over Time

In this alternative, a new constraint to limit the decrease of SN performance is included. For example, the constraint could be that the SN performance of the final year of analysis cannot be inferior than the SN performance of the base year. This alternative could represent a transportation agency that is starting to consider SN into the process but still gives priority to CS for treatment selection.

Alternative 2: Create a New Overall Performance Function that Incorporates CS and SN

In this alternative, a new overall performance function that combines the CS performance and the SN performance is created. This alternative works for a transportation agency that wants to explicitly introduce SN into the performance of the network. Equation 23 presents the linear combination proposed in this framework. Equation 23 has a weight factor μ that can be modified according to the priority of the agency. For example, when $\mu = 0.5$, both CS and SN are considered equally in the PMP process. When $\mu = 1$, the CS performance is considered only. When $\mu = 0$, the SN performance is considered only. Any other value of μ will give a higher weight either to the CS performance or the SN performance.

$$N_{Performance} = [\mu] * CS_{Performance} + [1 - \mu] * SN_{Performance} \quad (23)$$

Where,

$N_{Performance}$ = New Overall Performance Function

μ = Weight factor, $0 \leq \mu \leq 1$

$CS_{Performance}$ = CS performance for the network (for example, percentage of the road in Good or better condition)

$SN_{Performance}$ = SN performance for the network (for example, percentage of the road in Good friction)

Alternative 3: Redefine CS as CS* to Incorporate SN

In this alternative, the index CS is redefined to incorporate SN as a factor that affects the condition of pavement sections. This alternative works for transportation agencies that want to consider the impact of SN in the condition of the pavement and want to keep a single metric to measure the performance of the network. Equation 24 presents the definition of the new metric CS^* proposed in this framework. This equation includes the factor U_{SN}, which is the utility for a particular value of SN. The value of U_{SN} depends on a utility function defined for SN, and this function can be adapted to reflect the local conditions and priorities of the transportation agency.

$$CS^* = DS * U_{Ride} * U_{SN} \quad (24)$$

Where,

CS^* = Redefined Condition Score

DS = Distress Score

U_{Ride} = Utility value for the Ride Score

U_{SN} = Utility value for the Skid Number

Definition of Strategic Decisions and Goals

The strategic decisions and goals are the inputs provided by high-level decision makers regarding the expected performance that transportation agencies must achieve (Spy Pond Partners, High Street Consulting Group, Burns & McDonnell, 2019). In particular, four elements are essential for the PMP process:

- **Condition Ratings:** This is the definition of the condition of a pavement section based on the values of an index. For example, TxDOT uses CS ranges to define 5 conditions: Very Good, Good, Fair, Poor, and Very Poor (Table 13). A similar definition for SN values must be defined as well.
- **Performance Metrics:** This is the performance of the network. For example, TxDOT measures the performance as the percentage of the network in Good or better condition based on CS. A performance metric for SN must be defined as well.
- **Performance Targets:** This is the target (or goal) that it is expected to be achieved by the transportation agency within a reasonable period of time. For example, TxDOT's target is 90 percent of the pavements in Good or better condition. A performance target for SN must be defined as well.
- **Decision Rules for Treatment Selection:** These are the set of rules that will determine the type of treatment that a pavement section needs. Pavements have different types of distresses that can require different types of treatments. A set of rules to decide when to treat a section due to SN must be defined as well.

Network-level Asset Data

The network-level asset data is the pavement information of the network that will be used to predict the impacts of investments on performance (Spy Pond Partners, High

Street Consulting Group, Burns & McDonnell, 2019). In particular, the following elements need to be collected or defined for the analysis:

- **Network Inventory:** This is the inventory data of all the pavement sections that are part of the analysis. In the case of TxDOT, this information is in the Pavement Management Information Systems (PMIS).
- **Network Condition:** This includes all the pavement data that used to estimate the condition according to the definition provided in the "Strategic Decisions and Goals." This includes the Distress Score, utility value of the Ride Score, and Skid Number data. In the case of TxDOT, this information is included in the Pavement Management Information Systems (PMIS).
- **Treatment Levels:** These are the treatment alternatives that a pavement can received during the analysis period. Following the latest TxDOT's 4-Year PMP (TxDOT, 2018), the treatments at the network level are Preventive Maintenance, Light Rehabilitation, Medium Rehabilitation and Heavy Rehabilitation (Table 12).
- **Average Deterioration Rates:** These are the expected deterioration rates of the pavement sections and are one of the main drivers of the whole PMP process (Wiegmann & Yelchuru, 2012). TxDOT has its own deterioration models used for future prediction of pavement deterioration. In the case of Skid Number, network-level models as the one developed by Galvis Arce and Zhang (2019) can be used for predicting SN deterioration.
- **Performance Improvement After Treatments:** These are the expected condition after a pavement section receives a treatment. These performance improvements can be based on historical data. Some examples for Condition Score and Distress Score resets after a treatment are found in Gharaibeh, et al. (2012). For Skid Number, the resets can be found in Galvis Arce and Zhang (2020).

- **Network-Level Costs of Treatments:** These are the costs associated with each treatment level (PM, LR, MR, and HR). TxDOT's 4-Year PMP provides the latest values used for the network-level costs (TxDOT, 2018).

Optimization Process

The Optimization Process is the part of the framework where both sets of input ("Strategic Decisions and Goals" and "Network-Level Asset Data") are integrated for the analysis. This is a two-tier process. First, the Budget Planning analysis is performed, and then the Budget Allocation analysis is performed.

Perform Budget Planning Analysis

As mentioned earlier, Budget Planning is the process of defining the M&R program that would yield the minimum budget necessary to achieve a set of targets under given constraints (Zhang, 1996; Uddin, Hudson, & Haas, 2013). Table 15 presents a summary of the objective function and the constraints for the base scenario and the different alternatives. Both the base scenario and the alternatives have the objective function of minimizing the cost. However, the performance constraints differ for the base scenario and the alternatives. The base scenario is constrained to achieve the CS performance target only, while the alternatives include SN performance directly or indirectly in the constraints.

Table 15: Summary of the Objective Function and Performance Constraints for Budget Planning

Scenario	Objective Function	Performance Constraints
Base Scenario	$Min\ COST$	$CS_{Performance} \geq CS_{Target}$
Alternative 1 **(Limit SN Decline)**	$Min\ COST$	$CS_{Performance} \geq CS_{Target}$ $SN_{Performance} \geq SN_{Performance\ Base\ Year}$
Alternative 2 **(Linear combination)**	$Min\ COST$	$CS_{Performance} \geq CS_{Target}$ $SN_{Performance} \geq SN_{Target}$
Alternative 3 (CS*)	$Min\ COST$	$CS^{*}{}_{Performance} \geq CS^{*}{}_{Target}$

If the budget available is equal or greater than the budget needed, it is assumed that the agency will use the resources adequately and no other step is needed (as show in Figure 30). However, often times transportation agencies do not receive the budget needed and this is why the Budget Allocation process is performed.

Perform Budget Allocation Analysis

As mentioned earlier, Budget Allocation is the process of defining the M&R program that would yield the maximum performance of the network for a fixed budget under given constraints (Zhang, 1996; Uddin, Hudson, & Haas, 2013). Table 16 presents a summary of the objective function and the constraints for the base scenario and the different alternatives. The base scenario and alternative 1 have the same objective function of maximizing CS, while alternative 2 has the objective of maximizing the new performance function $N_{Performance}$. Alternative 3 has the objective of maximizing the new index $CS^{*}{}_{Performance}$. The base scenario and the alternatives have the constraint that the cost must be equal or less than the budget available, with alternative 2 having an additional constraint that the SN performance at the end of the analysis cannot be inferior than the SN performance at the base year, according to the definition of this alternative.

Table 16: Summary of the Objective Function and Budget and Performance Constraints for Budget Allocation

Scenario	**Objective Function**	**Budget and Performance Constraints**
Base Scenario	$Max\ CS_{Performance}$	$COST \leq BUDGET_{Available}$
Alternative 1 **(Limit SN Decline)**	$Max\ CS_{Performance}$	$COST \leq BUDGET_{Available}$ $SN_{Performance} \geq SN_{Performance\ Base\ Year}$
Alternative 2 **(Linear combination)**	$Max\ N_{Performance}$	$COST \leq BUDGET_{Available}$
Alternative 3 (CS*)	$Max\ CS^{*}{}_{Performance}$	$COST \leq BUDGET_{Available}$

Other Constraints Applicable to Budget Planning and Budget Allocation

There are other constraints that are applicable to the budget planning and budget allocation problem. These constraints are included in the analysis to reflect real world constraints and make the alternatives comparable:

- **Maximum percentage of sections that can be treated per year:** Even though a pavement section is identified as a candidate for treatment it does not mean that will be treated that year. There are some logistic constraints that can limit the number of sections that can be treated per year. For example, a treatment can be delayed if a whole corridor will be treated in the future or a utility work must be performed before the treatment. In this framework this percentage can be adjusted to reflect local conditions of the agency.
- **Sections can receive no more than one treatment during the 4-year time horizon:** It is unusual that a pavement section receives two or more treatments within 4 years, and it is even less likely that a pavement receives two consecutive treatments within two years. For these reasons this constraint is added to the optimization process.
- **Maximum percentage of the network in Very Poor condition:** Without this constraint, a possible solution of the optimization would be that 90 percent of the network is in Good or better condition while the remaining 10 percent is "abandoned" in Very Poor condition. This constraint limits the maximum number of pavement sections in Very Poor condition, which is something that transportation agencies aim. In this framework this percentage can be adjusted to reflect local conditions of the agency.

Compute Expected Condition

The result of the Budget Allocation process is the maintenance plan to be implemented during the analysis period. This maintenance plan can be used to estimate the overall condition of the network. If the expected condition of the network does not satisfy the expectations of the stakeholders, a change to the budget available, the constraints or the "Strategic Decisions and Goals" should be made, as indicated in the loop of Figure 30. Otherwise, the PMP process ends here.

Road Crashes and Other Costs Component

The results of the Budget Planning and Budget Allocation for the base scenario and the alternatives can be compared more comprehensively by including additional metrics in the analysis besides the performance and budget needed. For example, when planning for treatments that include improving SN, the budget needed is higher but the expected number of crashes is smaller. Therefore, comparing just the budget needed is an incomplete analysis. The following are the metrics are included in order to compare the different alternatives more comprehensively:

- **Performance Achieved:** The base scenario and alternatives will have different CS and SN performance achieved.
- **Budget Needed to Achieve the Targets:** In the case of Budget Planning, each alternative will have a different minimum budget needed in order to achieve their targets.
- **Expected Number of Crashes:** Each alternative will improve includes SN in a different way and will have different number of expected crashes. The expected number of crashes can be estimated using the SN condition of the network and the

CRR curves calibrated for the state of Texas (Wu, Zhang, Long, & Murphy, 2014; Galvis Arce & Zhang, 2020). The procedure to estimate the expected number of crashes is outlined in Chapter 3, in the section “Estimating Crash Reduction Per Year.”

- **Monetary Value of Expected Number of Crashes:** The monetary value of the expected number of crashes can be estimated using the societal and economic costs of the crashes and the crash severity distribution of Texas (U.S. DOT, 2020; Galvis Arce & Zhang, 2020). This process is outlined in Chapter 3, in the section “Estimate the Economic Benefits.”
- **Work Zone Road User Costs:** Each alternative will have a different number of lane-miles that would be treated each year, with the alternatives considering SN treating more sections. This increased in the number of sections to be treated has an economic impact on the congestion in the network, which is denominated the Work Zone Road User Costs (WZRUC). The monetary value of WZRUC can be estimated using the Federal Highway WZRUC manual (FHWA, 2011; Galvis Arce & Zhang, 2020). This process is outlined in Chapter 3, in the section “Estimate the Work Zone Road User Costs.”
- **Deferred Maintenance Cost:** These are the additional costs of future maintenance due to not reaching the target during the analysis period. In particular, these are the additional costs of performing higher treatment levels (Light Rehabilitation, Medium Rehabilitation, or Heavy Rehabilitation) instead of Preventive Maintenance. These costs occur because, when there is a limited budget, including SN in the analysis may reduce the number of sections to be treated when compared with analysis based on CS only. This framework follows the procedure proposed

by Jaipuria (2010), which estimates the additional costs using the base line of the CS goal (Equation 25).

$$DMC = \left(CS_{Target} - CS_{Performance}\right) * L * \sum_{i=1}^{I} u_i * \Delta Cost_i \quad (25)$$

Where,

DMC = Deferred maintenance cost

CS_{Target} = Condition Score performance target defined as part of the "Strategic Decisions and Goals"

$CS_{Performance}$ = Condition Score performance achieved

L = Total length of the network

u_i = Proportion of the network with Condition Score rating i

$\Delta Cost_i$ = Additional costs of treating pavement sections in Condition Score rating i compared to Preventive Maintenance

- **Vehicle Operation and Maintenance Costs:** These are the costs of operation and maintenance for vehicle owners. Research has shown that pavements in poor condition increase vehicle operation and maintenance expenses (Jaipuria, 2010; Chatti & Imen, 2012). In particular, the condition of the pavement has an impact on fuel, repair, maintenance and tires. When there is a limited budget, including SN in the analysis reduce the number of sections to be treated due to CS only. This framework follows the procedure proposed by Jaipuria (2010), which uses a multiplier to the vehicle operation and maintenance costs for worse pavement conditions, as shown in Equation 26.

$$VOMC = L * \sum_{i=1}^{I} \sum_{j=1}^{J} AADT * p_j * VOM_j * 365 * (1 + \alpha_i) * u_i \quad (26)$$

Where,

$VOMC$ = Total vehicle operation and maintenance costs

L = Total length of the network

$\sum_{i=1}^{I}$ = Sum over the different Condition Score ratings

$\sum_{j=1}^{J}$ = Sum over the different vehicle categories (e.g., small passenger cars, sedan, single-unit trucks, etc.)

$AADT$ = Average annual daily traffic

p_j = Proportion of vehicle category j

VOM_j = Vehicle operation and maintenance costs for vehicle category j

α_i = Multiplier of vehicle operation and maintenance costs for Condition Score rating i

u_i = Proportion of the network with Condition Score rating i

It is important to highlight that Budget Planning and Budget Allocation are solving two different problems; therefore, the metrics that can be used to compare the alternatives for each problem are different. Table 17 presents the metrics included for comparing the alternatives under Budget Planning and Budget Allocation.

Table 17: Summary of the Metrics Used to Compare Alternatives Under Budget Planning and Budget Allocation

Metric	Budget Planning	Budget Allocation
$CS_{Performance}$		✔
$SN_{Performance}$	✔	✔
Budget Needed	✔	
Expected Number of Crashes	✔	✔
Monetary Value of Expected Number of Crashes	✔	✔
Work Zone Road User Costs	✔	✔
Deferred Maintenance Cost		✔
Vehicle Operation and Maintenance Cost		✔

Another metric that can be estimated is the Benefit-Cost ratio (BCR) of choosing one of the alternatives over the base scenario. This BCR can be estimated as the ratio of the additional benefits due to crash reduction and the additional costs due to budget increase, WZRUC, deferred maintenance costs and vehicle operation and maintenance cost.

$$RBCR_i = \frac{\Delta Benefits}{\Delta Costs} = \frac{\Delta MVCR_i}{\Delta Budg_i + \Delta WZRUC_i + \Delta DMC_i + \Delta VOMC_i} \tag{27}$$

Where,

$RBCR_i$ = Relative Benefit-Cost Ratio of choosing one alternative i over the base scenario

$\Delta MVCR_i$ = Difference of the Monetary Value of Crashes between alternative i and the base scenario

$\Delta Budg_i$ = Difference of the budget needed between alternative i and the base scenario

$\Delta WZRUC_i$ = Difference of the Work Zone Road User Costs between alternative i and the base scenario

ΔDMC_i = Difference of the Deferred Maintenance Costs between alternative i and the base scenario

$\Delta VOMC_i$ = Difference of the Vehicle Operation and Maintenance Costs between alternative i and the base scenario

4.3 NUMERICAL CASE STUDY

Dataset Description

The dataset for the case study was obtained from the PMIS of the Texas Department of Transportation (TxDOT). Pavement attributes such as historical CS and SN measurements, and AADT, among others, were extracted for asphalt pavement sections from 2000 to 2015. A subset of 200 pavement sections from the Functional Group 3 (as defined in Chapter 3) were selected in order to have sections with similar characteristics.

Definition of Strategic Decisions and Goals

The Condition Score ratings used by TxDOT were for the case study (Table 13). In the case of Skid Number, Table 18 presents the ratings proposed based on the literature (Wu, Zhang, Long, & Murphy, 2014; Pratt, et al., 2014; Galvis Arce & Zhang, 2020). Table 19 present the performance metric and the performance target for CS and SN.

Table 18: Condition Ratings for Skid Number

Condition	Range
Good	$SN \geq 40$
Fair	$30 \leq SN < 40$
Poor	$20 \leq SN < 30$
Very Poor	$1 \leq SN < 20$

Table 19: Performance Metric and Performance Target for Condition Score and Skid Number

Index	**Performance Metric**	**Performance Target**
Condition Score	Percentage of the network in Good or better condition	90%
Skid Number	Percentage of the network in Fair or better friction	70%

The decision rules to select a treatment depend on the multiple distresses that a pavement section has. Currently, TxDOT has decision trees considering the different distresses and with multiple options for treatments. However, in this case study only network-level categories are considered (PM, LR, MR, and HR). For this reason, the decision rules for treatment selection were defined as shown in Table 20 (Jaipuria, 2010; Wu, Zhang, Long, & Murphy, 2014).

Table 20: Performance Metric and Performance Target for Condition Score and Skid Number

Index Range	$\boldsymbol{SN \geq 30}$	$\boldsymbol{1 \leq SN < 30}$
$\boldsymbol{CS \geq 90}$	Do Nothing	Preventive Maintenance
$\boldsymbol{70 \leq CS < 90}$	Preventive Maintenance	Preventive Maintenance
$\boldsymbol{50 \leq CS < 70}$	Light Rehabilitation	Light Rehabilitation
$\boldsymbol{35 \leq CS < 50}$	Medium Rehabilitation	Medium Rehabilitation
$\boldsymbol{1 \leq CS < 35}$	Heavy Rehabilitation	Heavy Rehabilitation

Network-Level Asset Data

TxDOT's network-level costs for the different treatment levels were used for the case study (Table 21) (TxDOT, 2018). The reset values for CS and SN after a treatment were defined to 100 for CS and 45 for SN based on historical data of the sample. The deterioration rates for CS were based on an extensive review of treatments and distresses over time for pavements summarized by Gharaibeh et al. (2012). The function was simplified as a piece-wise linear function, and the details are presented in Appendix A. The SN deterioration rates were estimated using the Markov Chain model for Functional Group 3, as outlined in Chapter 3. The details are presented in Appendix A.

Table 21: Network-Level Treatment Costs

Treatment Level	Cost
Preventive Maintenance	$50,000
Light Rehabilitation	$220,000
Medium Rehabilitation	$300,000
Heavy Rehabilitation	$470,000

For the utility function for SN (necessary for Alternative 3), a linear piece-wise function was selected. The function created was based on the current utility functions used by TxDOT (Goehl, 2014) and the safety analysis performed by Wu et al (2014). Figure 35 presents the utility function for SN used for the case study.

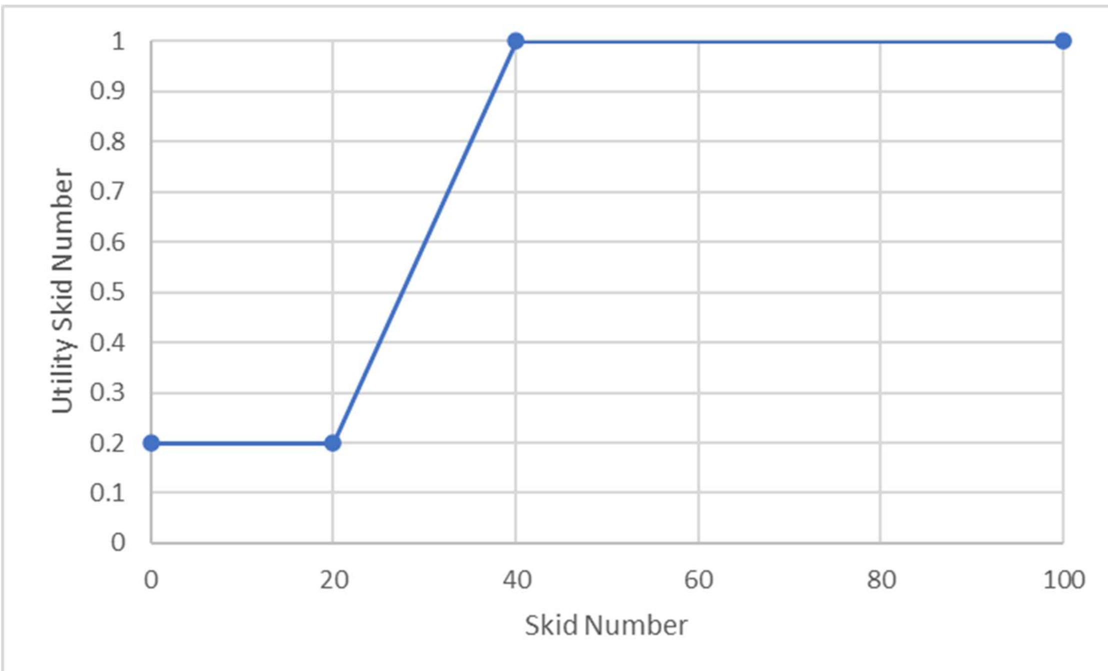

Figure 31: Utility Function for Skid Number Used for the Case Study

Results of the Budget Planning Analysis

Table 22 and Table 23 summarizes the results of the Budget Planning analysis. During the analysis it was found that the solution for the base scenario was also the most optimal solution for Alternative 1. In other words, when a transportation agency is aiming to improve the CS performance of the network, it is also avoiding a decline of SN performance. However, the improvement of SN performance tends to reach a maximum value and does not continue improving. After reviewing the data of the case study to explore this observation, it was found that there could be pavements with high CS (in other words, zero distresses) but with poor friction. When this happens, if the PMP process considers only CS, it does not identify the sections with high CS but poor friction as candidates for treatment. This example highlights the limitation of relying only on CS for the development of the PMPs.

Figure 36 presents the SN performance for the base scenario and the alternatives over the study period. An additional scenario of zero funding was added for reference. As can be seen in this figure, the SN performance for the base scenario and Alternative 1 increase at a slower pace than Alternative 2 and 3. In other words, including explicitly SN into the performance of the network (Alternatives 2 and 3) increases the overall SN performance at a faster rate than considering only CS.

Table 22: Results of the Budget Planning Analysis for the Base Scenario and the Alternatives

Comparison Metric	Base Scenario	Alternative 1 (Limit SN Decline)	Alternative 2 (Linear Combination)	Alternative 3 (CS*)
CS Performance	90%	90%	90.5%	95.5%
SN Performance	51.0%	51.0%	76.0%	90.0%
Budget Needs	$ 7,300,000	$ 7,300,000	$ 10,480,000	$ 10,940,000
Expected Number of Crashes	1458	1458	1343	1273
Monetary Value of Expected Number of Crashes	$ 204,090,000	$ 204,090,000	$ 188,030,000	$ 178,210,000
WZRUC	$ 237,106	$ 237,106	$ 353,357	$ 417,813
Relative BCR	0	0	4.9	6.8

Table 23: Percentage Change of Comparison Metrics with the Base Scenario as a Reference

Comparison Metric	**Alternative 1 (Limit SN Decline)**	**Alternative 2 (Linear Combination)**	**Alternative 3 (CS*)**
SN Performance	0%	49.0%	76.5%
Budget Needs	0%	43.6%	49.9%
Expected Number of Crashes	0%	-7.9%	-12.7%
Monetary Value of Expected Number of Crashes	0%	-7.9%	-12.7%
WZRUC	0%	49.0%	76.2%

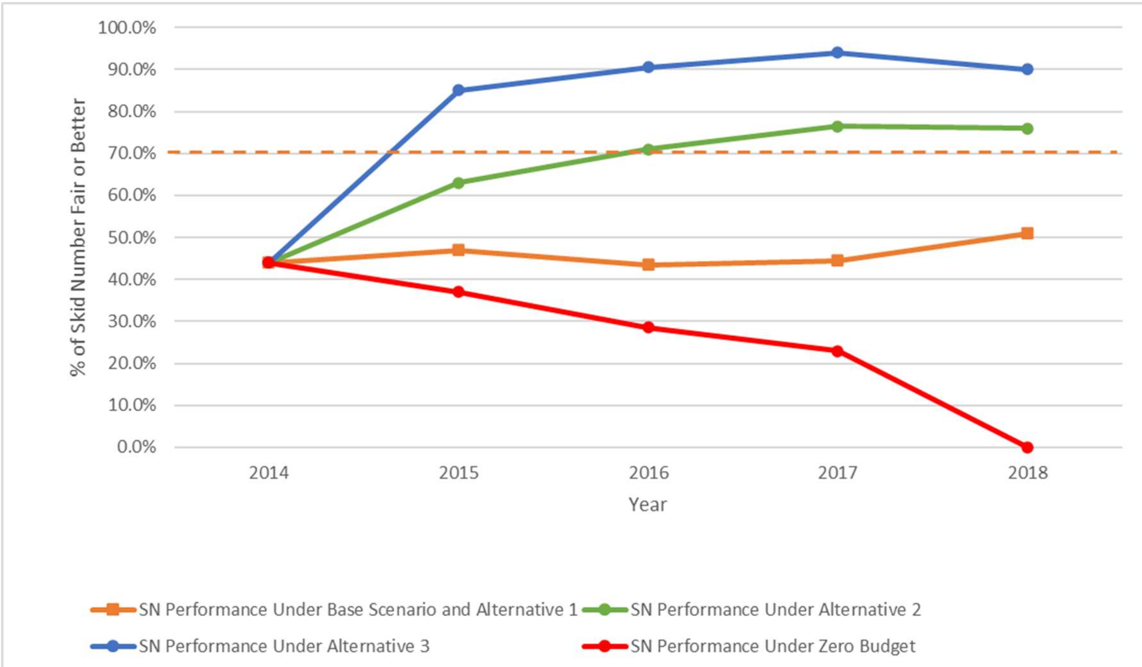

Figure 32: Skid Number Performance for the Base Scenario and the Alternatives Under Budget Planning

Table 23 shows that Alternative 2 and 3 increased the SN performance significantly. The increases are 49.0 percent for Alternative 2 and 76.5 percent for Alternative 3. These increases in the SN performance have an impact on road safety by reducing the expected number of crashes: the expected reduction is 7.9 percent and 12.7 percent for Alternative 2 and Alternative 3 respectively.

Table 23 also shows that the budget needed for Alternative 2 and 3 is higher than for the base scenario and Alternative 1. The increases in the budget needed are 43.6 percent 49.9 percent for Alternative 2 and Alternative 3 respectively. The reason for the increase of the budget needed is that both Alternatives 2 and 3 include more sections to be treated per year. However, Alternative 3 seems to be a more efficient alternative as it has a higher

SN performance and the costs are similar to Alternative 2. Similarly, Table 23 shows that Alternative 2 and 3 have a considerable increase in the congestion costs associated with work zones with increases of 49.0 percent and 76.2 percent respectively.

Table 22 includes the estimation of the relative BCR of the alternatives compared to the base scenario (according to Equation 26). Alternative 1 has a relative BCR of zero as it does not have additional benefits compared to the base scenario. Alternative 2 and 3 have a relative BCR of 4.9 and 6.8 respectively, showing that the additional benefits in terms of crash reduction outpaced the additional cost needed to implement them. Summaries of the treatment plan for the base scenario and the alternatives are presented in Appendix A.

Results of the Budget Allocation Analysis

To frame the Budget Allocation problem, it is assumed that the available budget is 90 percent of the needed budget estimated using the Budget Planning process. Table 24 and Table 25 summarizes the results of the Budget Allocation analysis. Similar to Budget Planning, it was found that the solution for the base scenario was also the most optimal solution for Alternative 1. In other words, the most optimal way to maximize CS performance and hold SN performance is effectively maximizing CS performance.

Table 24: Results of the Budget Allocation Analysis for the Base Scenario and the Alternatives

Comparison Metric	Base Scenario	Alternative 1 (Limit SN Decline)	Alternative 2 (Linear Combination)	Alternative 3 (CS*)
CS Performance	89.5%	89.5%	77.5%	85.5%
SN Performance	50.5%	50.5%	59.0%	60.5%
Expected Number of Crashes	1458	1458	1408	1410
Monetary Value of Expected Number of Crashes	$ 204,140,000	$ 204,140,000	$ 197,120,000	$ 197,460,000
WZRUC	$ 238,257	$ 238,257	$ 271,636	$ 277,391
Deferred Maintenance Costs	$ 35,350	$ 35,350	$ 1,767,500	$ 401,850
Vehicle Operation and Maintenance Costs	$ 219,299,003	$ 219,299,003	$ 221,361,123	$ 219,582,039
Relative BCR	0	0	1.8	9.7

Table 25: Percentage Change of Comparison Metrics with the Base Scenario as a Reference

Comparison Metrics	Alternative 1 (Limit SN Decline)	Alternative 2 (Linear Combination)	Alternative 3 (CS*)
CS Performance	0%	-13.4%	-4.5%
SN Performance	0%	16.8%	19.8%
Expected Number of Crashes	0%	-3.4%	-3.3%
Monetary Value of Expected Number of Crashes	0%	-3.4%	-3.3%
WZRUC	0%	14.0%	16.4%
Deferred Maintenance Costs	0%	4,900.0%	1,036.8%
Vehicle Operation and Maintenance Costs	0%	0.9%	0.1%

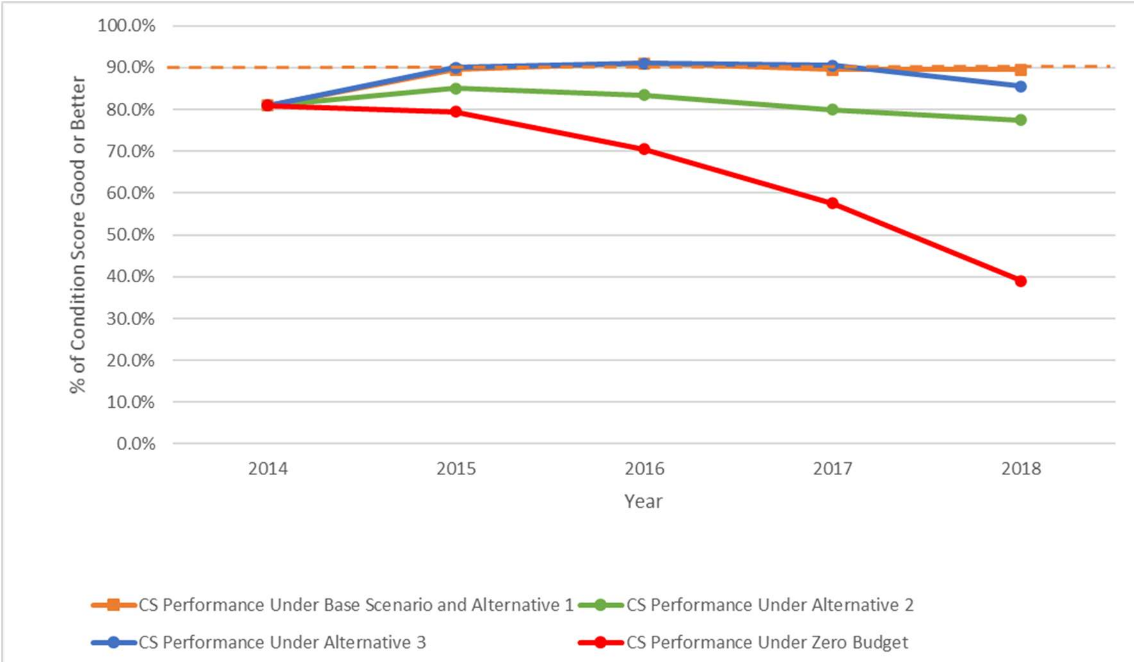

Figure 33: Condition Score Performance for the Base Scenario and the Alternatives Under Budget Allocation

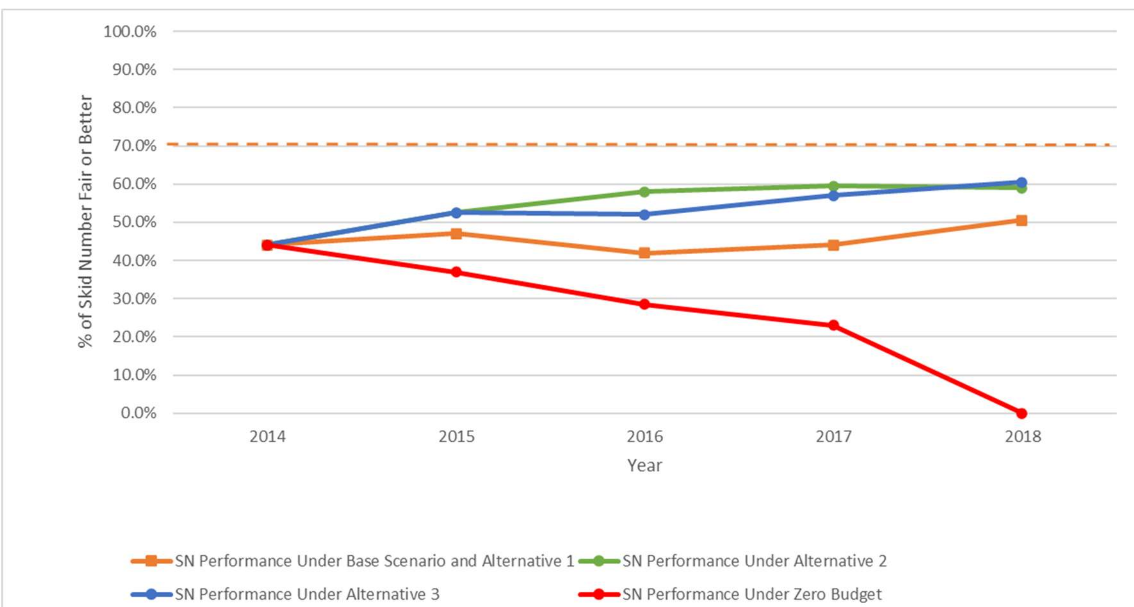

Figure 34: Skid Number Performance for the Base Scenario and the Alternatives Under Budget Allocation

Figure 33 presents the CS performance for the base scenario and the alternatives. As can be seen in this figure, under budget constraints, the base scenario and Alternative 3 perform very similar, while Alternative 2 has a slight decline in CS performance. In the case of SN performance (Figure 34) the opposite happens: Alternative 2 and 3 have a similar trend, while the base scenario has the lower SN performance.

These results show that Alternatives 2 and 3 improve SN performance at the cost of CS performance, although Alternative 2 has a higher impact on CS performance than Alternative 3. Table 25 shows that the CS performance of Alternative 3 is 3.9 percent below the base scenario, while Alternative 2 is 13.4 percent below. Table 25 also shows that the increases in SN performance are 16.8 percent and 19.8 percent for Alternative 2 and Alternative 3 respectively. These increases in the SN performance cause a reduction on the expected number of crashes, estimated in 3.4 and 3.3 percent for Alternatives 2 and 3 respectively.

Table 25 shows that, although the budget available is the same for the base scenario and the alternatives, Alternatives 2 and 3 increase significantly other costs. In particular, the highest increases are the deferred maintenance costs. These increases are 4,900.0 percent and 1,036.8 percent for Alternatives 2 and 3 respectively. In other words, with limited budget, incorporating SN-related targets would take a toll on CS performance, which ultimately will increase deferred maintenance costs. The second largest increases are the costs associated with congestion due to work zones, with 14.0 percent and 16.4 percent increases for Alternative 2 and 3 respectively. The lowest increases are the vehicle operation and maintenance costs, with less than 1 percent increase for both Alternatives 2 and 3.

Table 24 includes the estimation of the relative BCR of the alternatives compared to the base scenario. Alternative 1 has a BCR of zero as it does not have additional benefits compared to the base scenario. Alternative 2 and 3 have a relative BCR of 1.8 and 9.7 respectively, showing that, even when there is a constrained budget, the additional benefits in terms of crash reduction outpaced the additional costs needed to implement them. Summaries of the treatment plan for the base scenario and the alternatives are presented in Appendix A.

4.4 CONCLUSIONS

Currently, TxDOT and other transportation agencies do not incorporate pavement friction into the Pavement Management Process (PMP), although pavement friction data is collected regularly. This chapter explored three alternatives to incorporate SN into the PMP process. The main conclusions of this chapter are:

- There is a good opportunity to incorporate SN into the current PMP process. Moreover, such an incorporation can be implemented in multiple ways. In this paper, three alternatives are proposed, and each alternative modifies different aspects of the PMP process. For example, Alternative 1 keeps the CS and SN performance targets separated, while Alternative 2 creates a new overall performance function with both CS and SN performances. Alternative 3 does not change the performance metric or target, but does change the Condition Score index. This range of possibilities can help transportation agencies select the alternative that better suit their needs.
- There is a trade-off when SN is incorporated into the PMP process. In particular, for Budget Planning, there is a significant increase of the budget needs due to the inclusion of SN-related targets. In the case of Budget Allocation, although the budget available is the same across the alternatives, the inclusion of SN-related

targets has a toll on CS performance and ultimately increases deferral maintenance costs.

- Even though including the SN into the PMP process increases the costs (either budget needed or deferral maintenance costs), the benefits in terms of crash reduction are potentially higher. This finding is aligned with the literature that highlights the significant impact of SN on road crashes at the network level. Further work can be developed in this area by testing the proposed alternatives on a district- or state-scale network.

Appendix A

This appendix presents the details for some of the inputs and results for the case study of the proposed in Chapter 4 “Incorporating Skid Number into the Pavement Management Process.”

CONDITION SCORE DETERIORATION RATES

Condition Score is a composite index of the Distress Score and the utility value of the Ride Quality. A previous PMIS model from TxDOT provided curves for Distress Score deterioration over time. Gharaibeh, et al. (2012) conducted a review of these curves and proposed a set of curves for different climate-subgrade zones. Based on the curves for ACP pavements in Zone 2 from TxDOT’s classification, the deterioration was defined as a linear piece-wise function (Figure 36).

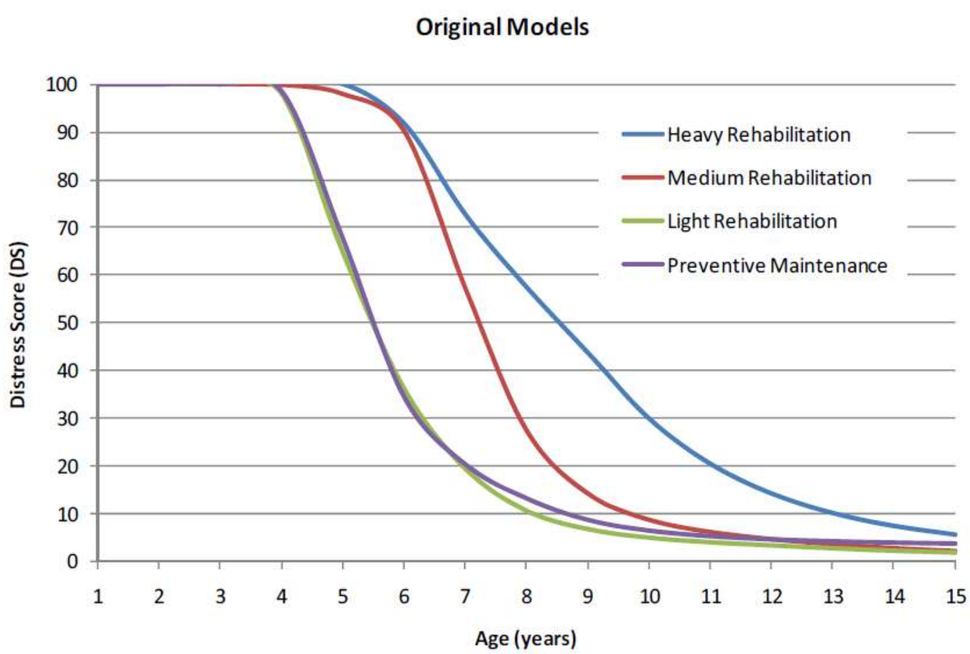

Figure 35: Previous Distress Score Models Used by PMIS (Gharaibeh, et al., 2012)

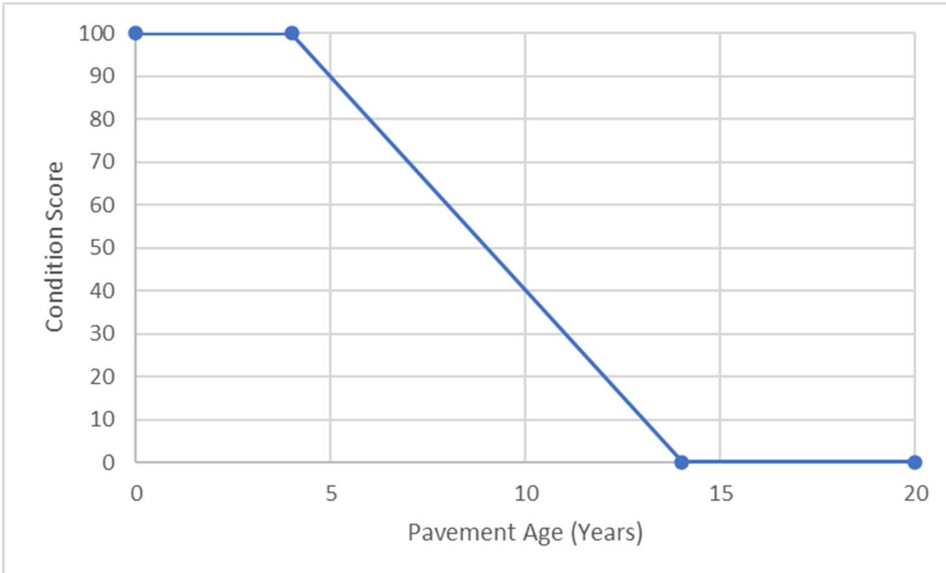

Figure 36: Condition Score Deterioration Rates Used for the Case Study

SKID NUMBER DETERIORATION RATES

For Skid Number deterioration, the Markov Chain for Functional Group 3 was used (Table 8). The deterioration was estimated as the product of the middle point of each condition state and the percentages predicted over time. This product estimates an "Equivalent SN value." Subsequently, this function was simplified into a linear piece-wise function. Figure 37 presents the Equivalent SN curve and Figure 38 the linear SN deterioration function used.

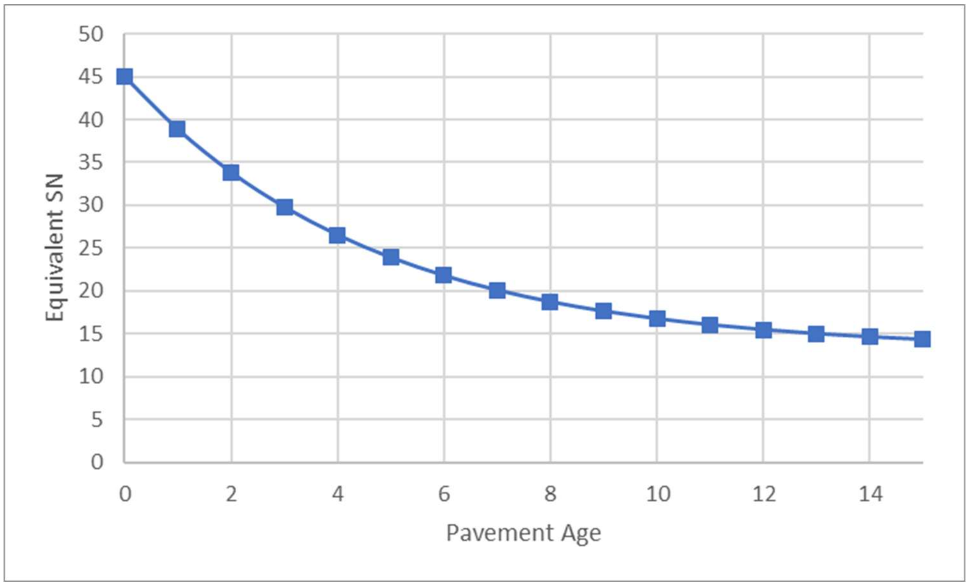

Figure 37: Equivalent SN as a Function of Pavement Age

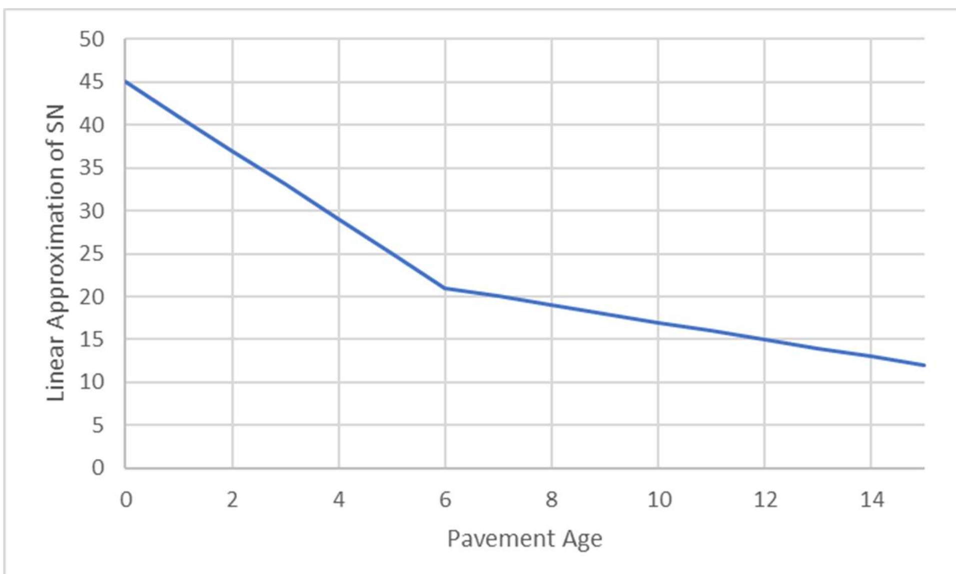

Figure 38: Skid Number Deterioration Rates Used for the Case Study

BUDGET PLANNING RESULTS

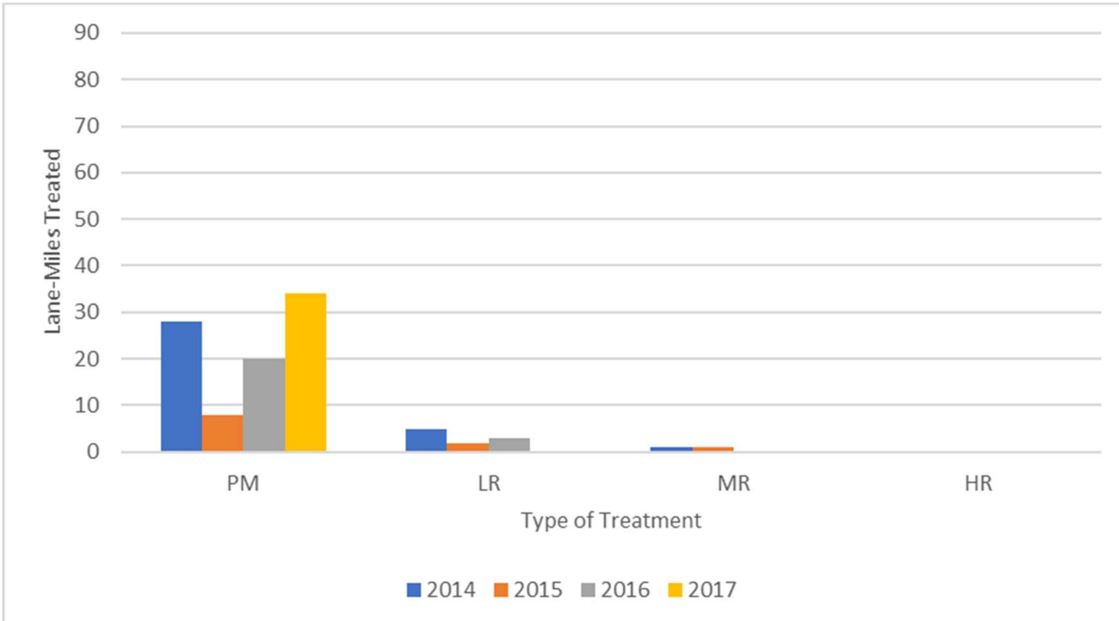

Figure 39: Summary of Treatments for the Base Scenario Under Budget Planning

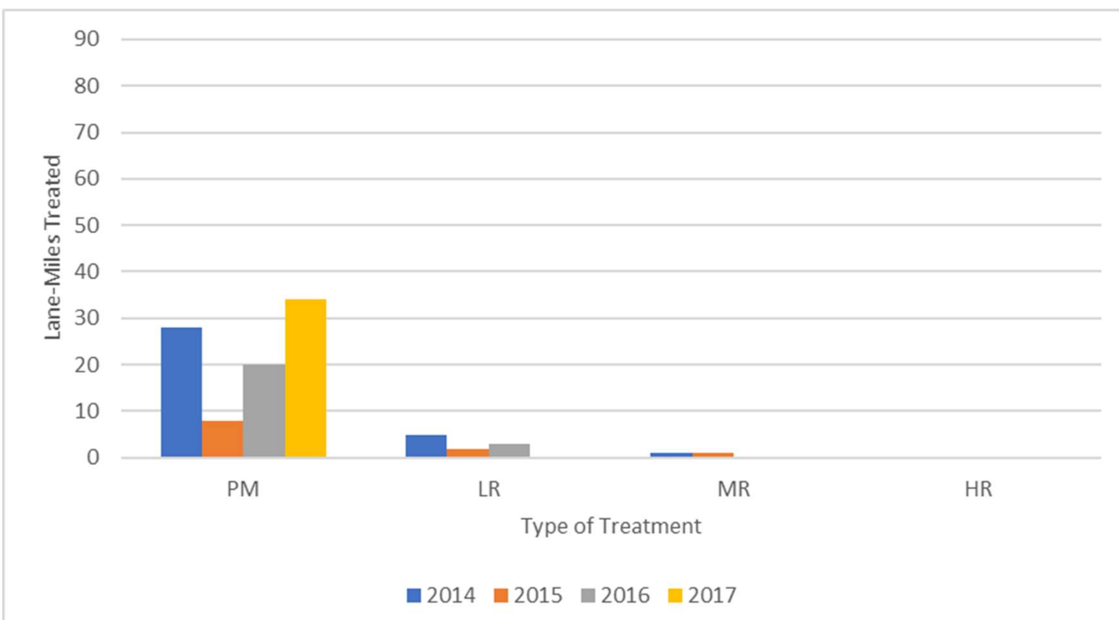

Figure 40: Summary of Treatments for Alternative 1 Under Budget Planning

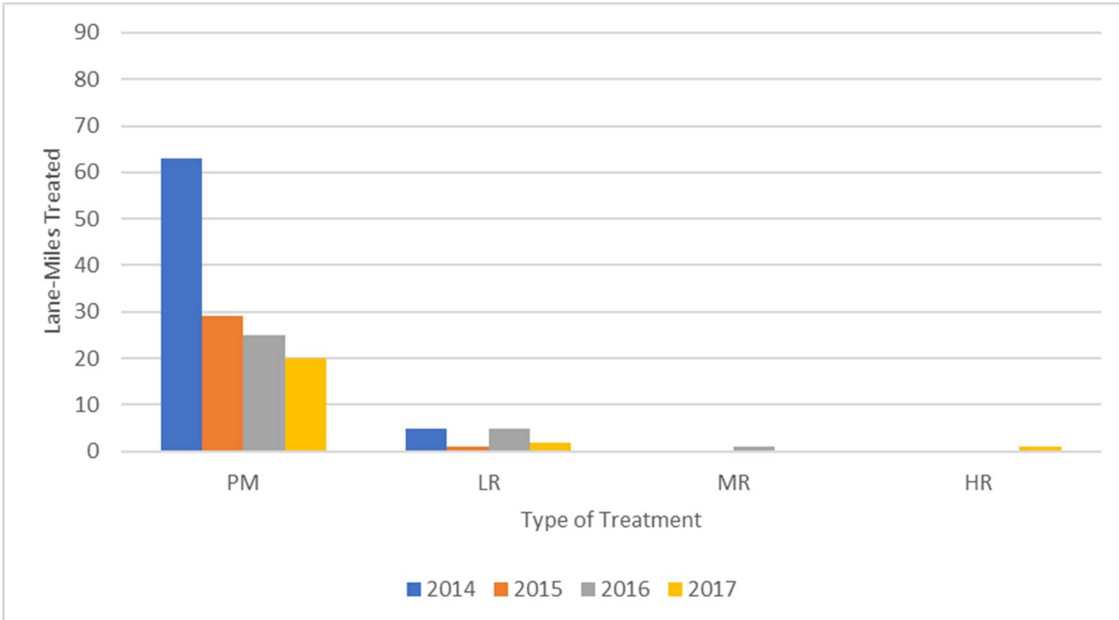

Figure 41: Summary of Treatments for Alternative 2 Under Budget Planning

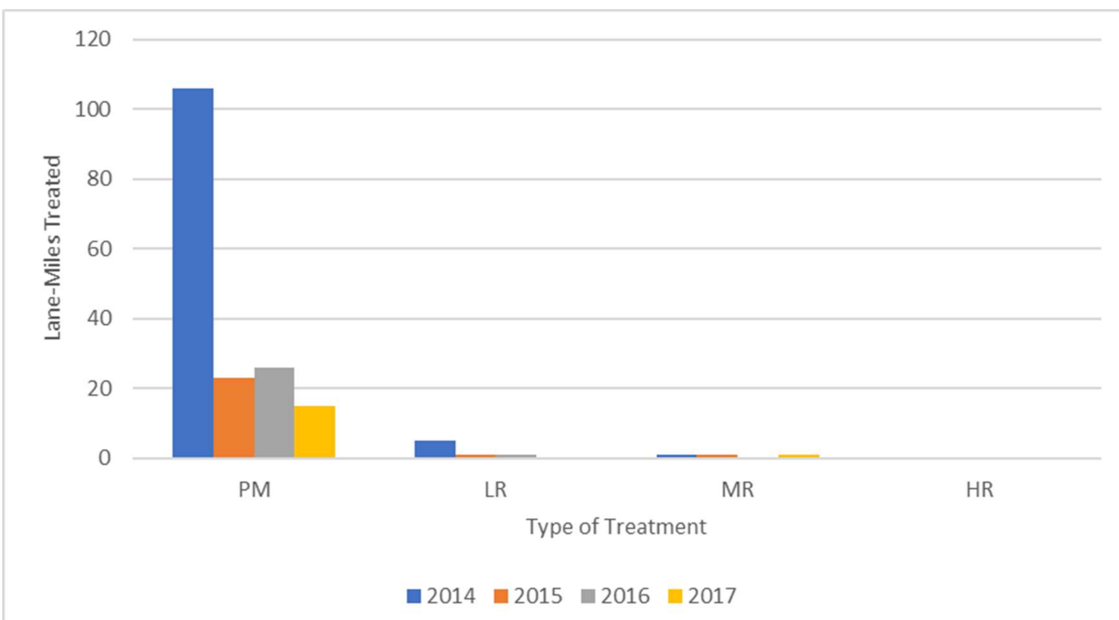

Figure 42: Summary of Treatments for Alternative 3 Under Budget Planning

BUDGET ALLOCATION RESULTS

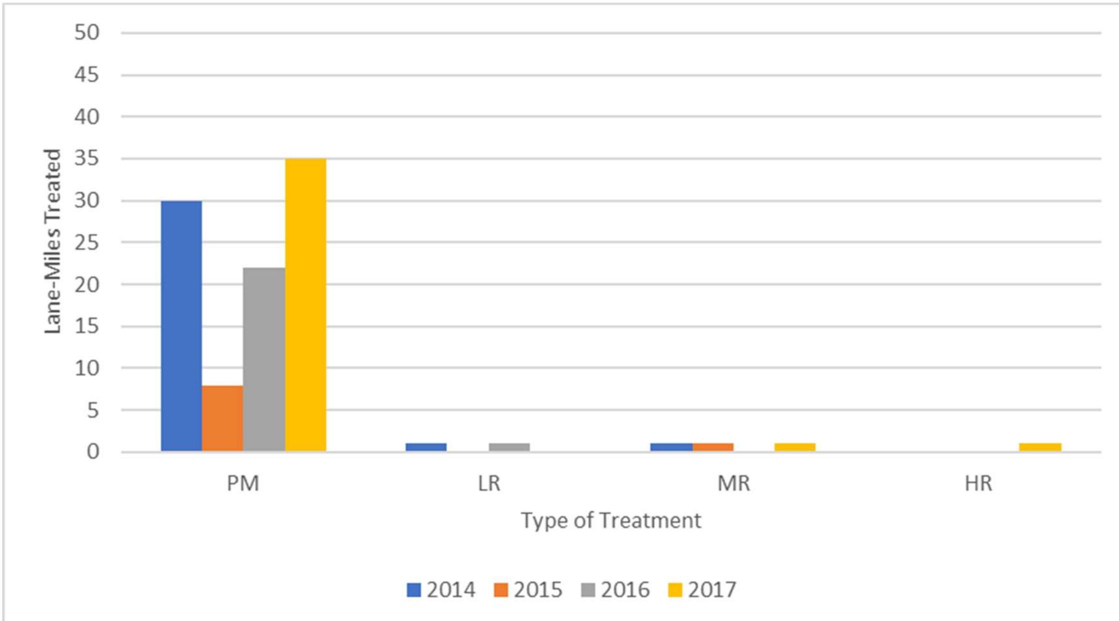

Figure 43: Summary of Treatments for the Base Scenario Under Budget Allocation

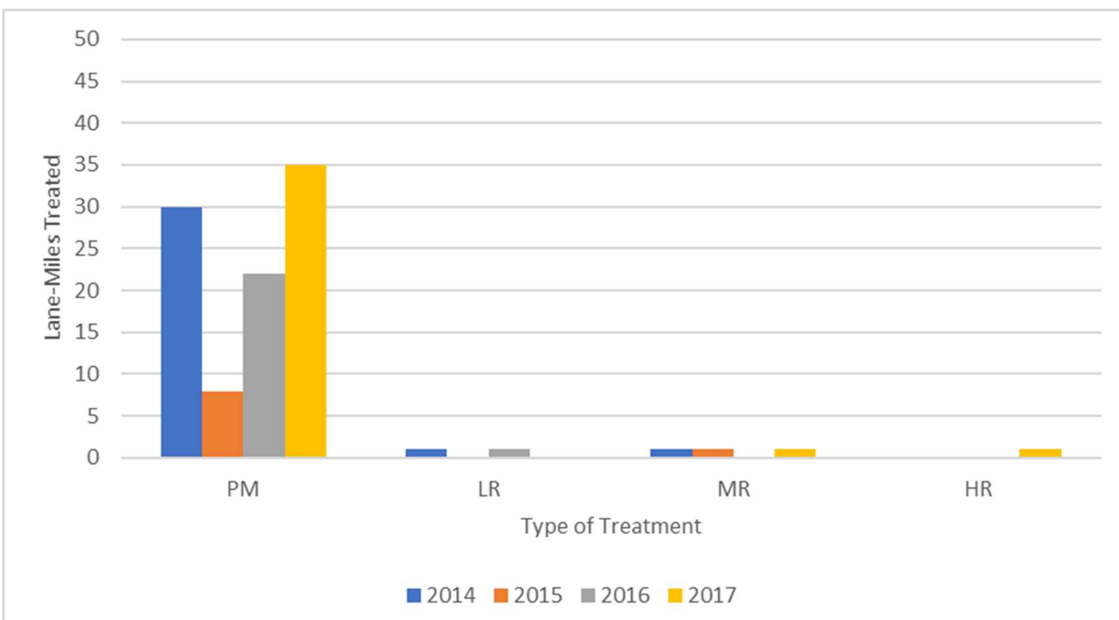

Figure 44: Summary of Treatments for Alternative 1 Under Budget Allocation

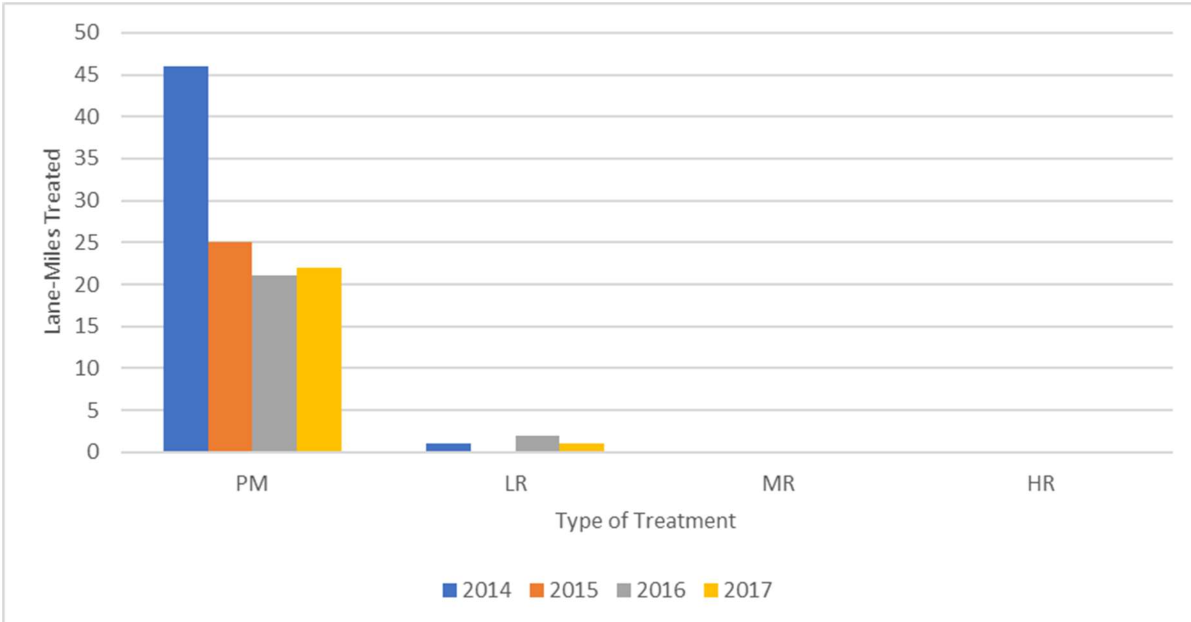

Figure 45: Summary of Treatments for Alternative 2 Under Budget Allocation

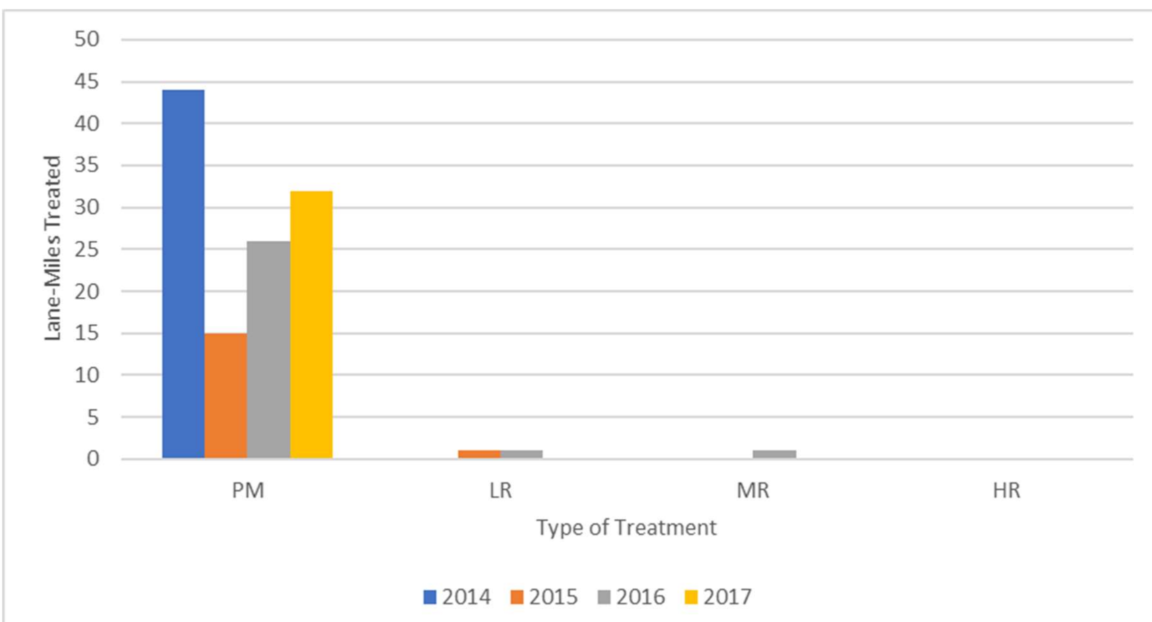

Figure 46: Summary of Treatments for Alternative 3 Under Budget Allocation

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