Framework to estimate the Benefit–Cost Ratio of establishing minimum pavement friction levels for roadway networks

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ABSTRACT
Low values of pavement friction increase crash rates. Some agencies such as FHWA and AASHTO have provided guidelines for the management of pavement friction, including the definition of minimum friction thresholds for roadway networks. 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 that quantified the BCR of establishing minimum friction thresholds. The objective of this paper is to fill this research gap by providing a methodology to quantify the BCR of establishing minimum friction thresholds for roadway networks. 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. The proposed framework was applied to a roadway network of 993 highway sections in Texas. The analysis was performed for Interstate Highways, Urban Freeways, and Arterials and Collectors. 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.

Background

Relationship between friction level and crashes
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 programmes to provide safer infrastructure to road users, including monitoring minimum friction levels for a roadway network.

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 SN (also called Friction Number (FN) in some states). The SN is an indirect standard measure that is described by the ASTM E274/E274M – 15 (ASTM International 2015).

Multiple researchers have concluded that low values of pavement friction (in terms of either SFC or SN) increase crash rates. McCullough and Hankins (1966) analysed 517 rural sections on Texas Highways and recommended a minimum level of pavement friction for Texas roads. 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. Geedipally (2006) analysed 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) analysed 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. 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) analysed 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.

Investigatory and intervention thresholds
Highway agencies usually manage their pavements at two levels: project level and network level (Haas et al. 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 analyse 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 NYS-DOT 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 SN505 (Skid Number measured at 50 mph with a Smooth tire) is below 20 (Wu et al. 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 paper, 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.

**Previous BCR 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.
In summary, 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 paper 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.

In order to accomplish this objective, the paper 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 paper.

Methodological framework
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 framework is depicted in Figure 1.

Modelling skid resistance deterioration
Modelling the skid resistance deterioration in the network is key to estimate the future condition in the network. In this paper, 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 condition vector \( u \), 3) the Deterioration Transition Probability Matrix (denoted as \( P \)), and 4) the Maintenance Transition Probability Matrix (denoted as \( M \)). These concepts are discussed in details as follows.

The first concept is the condition state. The condition states are the set of possible conditions in terms of SN and it is denoted by \( S = \{s_1, s_2, \ldots, s_r\} \), where \( r \) is the total number of condition states. The condition states were developed according to the following recommendations (Thompson et al. 2012, Galvis Arce and Zhang 2019):

1. Condition states must be ordered from the best condition to the worst condition;
2. Condition states must be contiguous;
3. Condition states can be defined using current state highways thresholds; and
4. Condition states must have enough observations for all the states defined in order to have a representative deterioration process.

The second concept is the condition vector \( u \). This vector \( u \) 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 \( u \) is \( r \).

The third concept is the Deterioration Transition Probability Matrix (\( P \)). The matrix \( P \) contains the annual probabilities that the SN of a section will deteriorate from a better condition to a worse condition. In general, \( P \) follows the matrix presented in Equation (1) in a natural deterioration process. The \( p_{ij} \) values represent the probabilities that the SN will remain in the same condition state. The \( p_{ij} \) values where \( j > i \) represent the probabilities that the SN will deteriorate from condition state \( i \) to condition state \( j \). The values of zero represent the fact that, unless maintenance is applied, the SN of a pavement will not improve its condition. Finally, the value of \( p_{rr} = 1 \) represents the fact that once a pavement achieves the worst SN condition, it will remain in that condition unless a treatment is applied. Other properties of \( P \) are that \( 0 \leq p_{ij} \leq 1 \) and \( \sum_{j=1}^{r} p_{ij} = 1 \).

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

The fourth concept is the Maintenance Transition Probability Matrix (\( M \)). The matrix \( M \) 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, \( M \) follows the matrix presented in Equation (2) (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 \( P \), other properties of \( M \) are that \( 0 \leq m_{ij} \leq 1 \) and \( \sum_{j=1}^{r} m_{ij} = 1 \).

\[
M = \begin{bmatrix}
    m_{11} & 0 & \cdots & 0 \\
    m_{21} & m_{22} & \cdots & 0 \\
    \vdots & \vdots & \ddots & \vdots \\
    m_{r1} & m_{r2} & \cdots & m_{rr}
\end{bmatrix} \tag{2}
\]

The vector \( u \) and the matrices \( P \) and \( M \) are used to estimate the future condition of the network. Equation (3) presents the estimation when there is natural deterioration and Equation (4) for the case when maintenance actions are taken.

\[
u_k = u_0 \cdot (P)^k \tag{3}
\]

Where:
\( u_k = \) Condition vector, year \( k \).
\( u_0 = \) Initial condition vector.
\( P = \) Deterioration Transition Probability Matrix.

\[
u_k = u_0 \cdot (M \cdot P)^k \tag{4}
\]

Where:
\( u_k = \) Condition vector, year \( k \).
**u₀** = Initial condition vector.

**M** = Maintenance Transition Probability Matrix.

**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 et al. 2010, Smith et al. 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 Sub-sampling, or Bootstrap (Galvis Arce 2017). In general, these

**Figure 1.** Framework for the Estimation of the Benefit-Cost Ratio of Establishing a Friction Intervention Threshold.

**Figure 2.** Example of the K-Fold Cross-Validation for *K* = 4.
methods use a portion of the data for training the model (that is, to 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 is used for training the model and the remaining data is used for testing. This process is repeated K times, each time changing the dataset that is tested (Figure 2). In this paper, K equals 4. After K iterations, the matrix P is estimated.

For validating the model (the remaining 20 percent of the data), the Chi-Square (χ²) 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 pij of P are estimated using the ‘counting proportions’ formula Equation (5) (Galvis Arce and Zhang 2019). The parameters of the matrix P are the average of the K estimations.

\[ \hat{p}_{ij} = \frac{N_{ij}}{\sum_{j=0}^{r} N_{ij}} \]

Where: \( \hat{p}_{ij} \) = Estimated annual transition probability from condition state \( i \) to state \( j \).
\( N_{ij} \) = Number of observed transitions from state \( i \) to state \( j \).
\( \sum_{j=0}^{r} N_{ij} \) = Total number of observed transitions from state \( i \) to all the states in \( S \).

Previous researchers have found that the accuracy of the prediction of \( \hat{P} \) can be improved using optimisation (Butt et al. 1987, Jiang et al. 1989, Galvis Arce and Zhang 2019). The optimisation objective is to minimise the error between the observed values of the testing set and the predicted values estimated using Equation (3). The objective function used in this paper is presented in Equation (6). The Generalized Reduced Gradient (GRG) Non-linear algorithm, which is included in Microsoft Excel, was used to optimise Equation (6).

\[ \text{Min} \sum_{k=1}^{r} \sum_{i=1}^{r} \frac{(u_{i,k} - \hat{u}_{i,k})^2}{\hat{u}_{i,k}} \]

Where:
\( u_{i,k} \) = Observed condition state probability \( i \) of the testing set at iteration \( k \).
\( \hat{u}_{i,k} \) = 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 optimised matrix \( \hat{P} \), the future condition of the validation dataset is estimated using Equation (3). Then, the Chi-Square (χ²) statistic is estimated according to Equation (7).

\[ \chi^2 = \sum_{i=1}^{r} \frac{(O_i - E_i)^2}{E_i} \]

Where:
\( O_i \) = Observed pavement sections in condition state \( i \) from the validation dataset.
\( E_i \) = Predicted pavement sections in condition state \( i \) from the validation dataset.
\( r \) = Total number of condition states.

For the Chi-Square (χ²) 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, \( \alpha \) is set to 0.05. Therefore, if the \( p \)-value of the test is smaller than \( \alpha \), \( H_0 \) 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 costs**

The costs are estimated as 1) the budget needed to treat the pavement sections for which friction levels drop below the intervention threshold, 2) the monetary value of travel time delays in the roadways due to the treatments, and 3) the monetary value of road safety risks due to the presence of work zones. 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 \( u_0 \) and the matrices \( P \) and \( M \) are used to estimate the future condition of the network as shown in Equation (4). The matrix \( M \) is defined based on the treatment applied and the minimum SN threshold defined (the threshold in which an action is taken). One assumption that is implicit in Equation (4) 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 (8).

\[ LM_k = \sum_{i=1}^{r} \sum_{j=1}^{r} m_{ij} u_{i,j} \]

Where:
\( LM_k \) = Number of lane miles to be treated in year \( k \).
\( \sum_{j=1}^{r} \) = Sum over all the condition states.
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 (5). This average cost is a representative value of the treatment costs per lane mile in the network.

\[ \text{CO}_k = \text{LM}_k \times \text{UCT} \]  

(9)

Where:
- \( \text{CO}_k \) = Maintenance costs in year \( k \).
- \( \text{LM}_k \) = Number of lane miles to treat in year \( k \).
- \( \text{UCT} \) = 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. At this section of the highway the normal traffic flow on the road is 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’ (WZRUC) (FHWA 2011).

Although the type of impacts depends on the type of work to be performed, in general WZRUC can be categorised 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 summarised 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 3 presents the process to estimate the Work Zone.
state using historical data. In this paper, crash rates per million VMT for each condition state are estimated using historical data.

**Estimate the reduction of crashes**

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 (12).

\[
CR_k = \sum_{i=1}^{r} (u_{k,i} \times N \times R_i \times VMT) \tag{12}
\]

Where:
- \(CR_k\) = Expected number of crashes in the network in year \(k\).
- \(r\) = Total number of condition states.
- \(u_{k,i}\) = 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 \(i\).
- \(VMT\) = Average traffic VMT (in million).

**Estimate the economic benefits**

The annual economic benefits are estimated as show in Equation (13). The benefits are the product of \(a\) the expected reduction of crashes in the network, and \(b\) the average cost per crash Equation (11).

\[
BE_k = (CR_k - CR_k^{SN}) \times ACC \tag{13}
\]

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 (14).

\[
BCR^{SN} = \frac{\sum_{k=1}^{T} BE_k}{\sum_{k=1}^{T} CO_k} \tag{14}
\]

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 \(k\).

**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 recorded SN transitions over the years 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 Beneﬁts. Once the values are adjusted, the BCR is estimated as shown in Equation (14).

**Modelling skid resistance deterioration**

Skid Number deterioration was analysed by traffic AADT and Functional System Class in order to define homogenous
Table 1. Sources to Estimate the Work Zone Delay and Depreciation Costs.

<table>
<thead>
<tr>
<th>Item</th>
<th>Source</th>
<th>Specific Source</th>
<th>Formula (If Applies)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost per Hour of Personal Travel</td>
<td>U.S. Census Bureau (2018) American Community Survey Briefs</td>
<td>Median Household Income from the American Community Survey Briefs by state</td>
<td>Local: 50% of median household annual income / 2,080 h ($2017) Intercity: 70% of median household annual income / 2,080 h ($2017)</td>
<td>Local: $14.23 Intercity: $19.93</td>
</tr>
<tr>
<td>Cost per Hour of Single-Unit Trucks</td>
<td>U.S. Bureau of Labor Statistics – Occupational Employment Statistics (2018) and Employer Costs for Employee Compensation Summary (2020)</td>
<td>Median hourly wages and benefits of category &quot;Light Truck or Delivery Services Drivers&quot; by state</td>
<td>100% of the median hourly wages and benefits</td>
<td>$23.08</td>
</tr>
<tr>
<td>Average Vehicle Occupancy on Personal Travel</td>
<td>FHWA (2018) National Household Travel Survey</td>
<td>Average Vehicle Occupancy, &quot;All Purposes&quot;</td>
<td>None</td>
<td>1.67</td>
</tr>
<tr>
<td>Average Vehicle Occupancy on Business Travel</td>
<td>FHWA (2018) National Household Travel Survey</td>
<td>Average Vehicle Occupancy, &quot;To/From Work&quot;</td>
<td>None</td>
<td>1.18</td>
</tr>
<tr>
<td>Average Vehicle Occupancy on Single-Unit Trucks</td>
<td>FHWA (2011) Work Zone Road User Costs</td>
<td>National Averages</td>
<td>None</td>
<td>1.05</td>
</tr>
<tr>
<td>Average Vehicle Occupancy on Combination of Trucks</td>
<td>FHWA (2011) Work Zone Road User Costs</td>
<td>National Averages</td>
<td>None</td>
<td>1.12</td>
</tr>
<tr>
<td>Proportion of Passenger Cars that are Personal Travel</td>
<td>Bureau of Transportation Statistics (2020)</td>
<td>&quot;Transportation by the Numbers&quot; report per state, passenger travel by trip purpose</td>
<td>None</td>
<td>98.50%</td>
</tr>
<tr>
<td>Proportion of Passenger Cars that are Business Travel</td>
<td>Bureau of Transportation Statistics (2020)</td>
<td>&quot;Transportation by the Numbers&quot; report per state, passenger travel by trip purpose</td>
<td>None</td>
<td>1.50%</td>
</tr>
<tr>
<td>Proportion of Trucks that are Single-Unit Trucks</td>
<td>FHWA (2020) Highway Performance Monitoring System (HPMS) Sample</td>
<td>Average Single-Unit Trucks as a proportion of Truck AADT by Functional System Class</td>
<td>None</td>
<td>Estimated for the case study</td>
</tr>
<tr>
<td>Proportion of Trucks that are Combination of Trucks</td>
<td>FHWA (2020) Highway Performance Monitoring System (HPMS) Sample</td>
<td>Average Combination of Trucks as a proportion of Truck AADT by Functional System Class</td>
<td>None</td>
<td>Estimated for the case study</td>
</tr>
<tr>
<td>Passenger Car AADT</td>
<td>Local sources</td>
<td>Obtained from sections analysed</td>
<td>None</td>
<td>Estimated for the case study</td>
</tr>
<tr>
<td>Truck AADT</td>
<td>Local sources</td>
<td>Obtained from sections analysed</td>
<td>None</td>
<td>Estimated for the case study</td>
</tr>
<tr>
<td>Depreciation Costs Per Hour Passenger Cars</td>
<td>FHWA (2011) Work Zone Road User Costs</td>
<td>Depreciation costs per hour for medium-sized to large autos ($2010)</td>
<td>None</td>
<td>$1.40</td>
</tr>
<tr>
<td>Depreciation Costs Per Hour Single-Unit Trucks</td>
<td>FHWA (2011) Work Zone Road User Costs</td>
<td>Depreciation costs per hour for four-tire single-unit trucks ($2010)</td>
<td>None</td>
<td>$2.58</td>
</tr>
<tr>
<td>Depreciation Costs Per Hour Combination of Trucks</td>
<td>FHWA (2011) Work Zone Road User Costs</td>
<td>Depreciation costs per hour for 5+ axles trucks ($2010)</td>
<td>None</td>
<td>$8.70</td>
</tr>
<tr>
<td>Produce Price Index Adjustment (If Needed) for Passenger Cars</td>
<td>U.S. Bureau of Labor Statistics (2020b) Produce Price Index</td>
<td>PPI for passenger cars (Item # 141101)</td>
<td>PPI2014 / PPI2010</td>
<td>0.9262</td>
</tr>
<tr>
<td>Produce Price Index Adjustment (If Needed) for Single-Unit Trucks</td>
<td>U.S. Bureau of Labor Statistics (2020b) Produce Price Index</td>
<td>PPI for trucks, 14,000 lbs. and under (Item # 141105)</td>
<td>PPI2014 / PPI2010</td>
<td>1.2093</td>
</tr>
<tr>
<td>Produce Price Index Adjustment (If Needed) for Combination of Trucks</td>
<td>U.S. Bureau of Labor Statistics (2020b) Produce Price Index</td>
<td>PPI for trucks, over 14,000 lbs. GVW (Item # 141106)</td>
<td>PPI2014 / PPI2010</td>
<td>1.0030</td>
</tr>
</tbody>
</table>

Figure 4. Process to Estimate the Depreciation Costs for 1) Passenger Cars, 2) Single-Unit Trucks, and 3) Combination of Trucks.
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 5: 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 2.

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 3 presents the matrix \( P \) obtained for the three groups after validation.

**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 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 (Pratt et al. 2014, Chowdhury et al. 2017). Therefore, in the matrix \( M \), 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 analysed. 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 mobilisation of equipment to the treatment location, traffic control, labour, 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

**Table 3. Deterioration Transition Probability Matrix (Matrix \( P \)) of the MC Model.**

<table>
<thead>
<tr>
<th>Condition State</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.768</td>
<td>0.232</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>0.000</td>
<td>0.494</td>
<td>0.506</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>3</td>
<td>0.000</td>
<td>0.000</td>
<td>0.758</td>
<td>0.201</td>
<td>0.040</td>
</tr>
<tr>
<td>4</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.879</td>
<td>0.121</td>
</tr>
<tr>
<td>5</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

**Table 2. Condition States Defined for the Case Study.**

<table>
<thead>
<tr>
<th>Condition State</th>
<th>Lower SN Bound</th>
<th>Upper SN Bound</th>
<th>Crash Rate per Million VMT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>51</td>
<td>100</td>
<td>0.866</td>
</tr>
<tr>
<td>2</td>
<td>41</td>
<td>50</td>
<td>0.861</td>
</tr>
<tr>
<td>3</td>
<td>31</td>
<td>40</td>
<td>1.022</td>
</tr>
<tr>
<td>4</td>
<td>21</td>
<td>30</td>
<td>1.135</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>20</td>
<td>1.498</td>
</tr>
</tbody>
</table>

**Figure 5. SN Deterioration Rates presented as a) Distribution of SN Annual Deterioration, and b) Cumulative SN Annual Deterioration.**
depreciation costs for each functional system group are presented in Table 4. 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 et al. 2008). This CMF can be accessible in the CMF clearinghouse database of FHWA.

**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 2 and Figure 6.

The average cost per crash was estimated using: a) the distribution of crash severity in the state of Texas in 2012 (TxDOT 2019), 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 was estimated as shown in Equation (11) and the result is presented in Table 5.

**BCR estimation**

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 7 presents the results for the three functional system groups analysed for comparison purposes while Figures 8–10 presents the results separately for Interstate Highways, Urban Freeways and Arterials and Collectors respectively.

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.

---

**Table 4.** Total Delay and Depreciation Costs per Vehicle Per Section Treated.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0.22</td>
<td>$0.18</td>
<td>$0.26</td>
</tr>
<tr>
<td>2</td>
<td>$0.20</td>
<td>$0.22</td>
<td>$0.32</td>
</tr>
<tr>
<td>3</td>
<td>$0.20</td>
<td>$0.22</td>
<td>$0.32</td>
</tr>
</tbody>
</table>

**Table 5.** Distribution of Crash Severity in Texas in 2012 and Their Respective Costs for Safety Analysis.

<table>
<thead>
<tr>
<th>KABCO LEVEL</th>
<th>Monetized Value ($2018)</th>
<th>Monetized Value ($2014)</th>
<th>Number of People (for “Unknown if Injured” is the Number of Accidents)</th>
<th>Cost by Severity ($2014)</th>
</tr>
</thead>
<tbody>
<tr>
<td>O – No Injury</td>
<td>$3,200</td>
<td>$3,004</td>
<td>46,584</td>
<td>$139,918,153</td>
</tr>
<tr>
<td>C – Possible Injury</td>
<td>$63,900</td>
<td>$59,977</td>
<td>8,832</td>
<td>$529,721,044</td>
</tr>
<tr>
<td>B – Non-Incapaciting Injury</td>
<td>$125,000</td>
<td>$117,327</td>
<td>7,175</td>
<td>$841,819,974</td>
</tr>
<tr>
<td>A – Incapaciting Injury</td>
<td>$459,100</td>
<td>$430,918</td>
<td>1,311</td>
<td>$564,933,452</td>
</tr>
<tr>
<td>K – Killed</td>
<td>$9,600,000</td>
<td>$9,010,700</td>
<td>215</td>
<td>$1,937,300,544</td>
</tr>
<tr>
<td>U – Injured (Severity Unknown)</td>
<td>$174,000</td>
<td>$163,319</td>
<td>3,096</td>
<td>$505,635,442</td>
</tr>
<tr>
<td># Accidents Reported (Unknown if Injured)</td>
<td>$132,200</td>
<td>$124,085</td>
<td>942</td>
<td>$116,887,929</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$4,636,216,538</strong></td>
<td><strong>$4,394,268</strong></td>
<td><strong>25,068</strong></td>
<td><strong>$185,000</strong></td>
</tr>
</tbody>
</table>

**Figure 6.** Crash Rates per Million VMT as a Function of Skid Number in the Case Study Network.
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 et al. 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 are valid only for a network where an agency is applying the intervention threshold strategy. 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 39.6–20.0 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 11 and Table 6. The middle points are used because of the discontinuity caused when the SN was grouped in condition states. Figure 11 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.
due to traffic disruptions can also be considered in the BCR analysis.

(3) The scope of the paper is to estimate the BCR when an agency is applying the intervention threshold strategy (that is, treating only the sections with friction levels below a defined threshold). Therefore, the results are valid only for a network where an agency is applying the intervention threshold strategy. This paper does not assess if the intervention threshold strategy is the best maintenance strategy to manage skid resistance. Further research is needed in this area in order to estimate the cost-effectiveness of different maintenance strategies and to compare different policies aiming to manage skid resistance at the network level.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

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