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Investigation on Framework to Estimate the Benefit Cost Ratio of Establishing Minimum Pavement Friction Levels

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Abstract- In this study, we present a framework for calculating the BCR and setting the threshold at which to initiate SN treatment. Using an MC degradation model, the suggested method quantifies the number of lane miles that must be addressed in order to assess the network's maintenance cost. Indirect expenses included things like lost time at work and accidents caused by traffic congestion. A monetary value for the benefit was determined by using reductions in crash rates per vehicle mile traveled. Here's a brief summary of what we discovered: (1) This paper's major novel contribution is an analytical framework that can be utilized by transportation organizations to estimate the BCR of maintenance plans that aim to offer a minimal SN in a highway network. This evaluation is supposed to be duplicated in a variety of settings, unlike previous studies that depended on engineers' subjective opinion, assumed values, or local experience to establish either the treatment cost or the benefit of crash reduction. The study may be modified by changing the economic variables used to take into account regional differences. As such, the goal of this study is to provide an estimate of the BCR in situations where an agency employs the intervention threshold approach (i.e., only treats segments with friction levels below a specific threshold). These results are limited to networks in which an agency applied an intervention threshold approach since no additional networks were considered. This investigation does not assess the efficacy of the intervention threshold strategy for controlling skid resistance.

Keywords-BCR, Specific threshold, analytical framework etc.

I. INTRODUCTION

1. Background

The frequency of automobile accidents and the resulting frictional losses constitute a global health emergency. Over 35,000 people were killed and over 3 million were wounded in road accidents in the United States in 2016 (NHTSA 2019). This is why governments at all levels of transportation work tirelessly to enhance their policies and facilities for the sake of driver safety. The Sideways Force Coefficient (SFC) and the Skid Number (SN) are two common measures of pavement friction. The SFC is widely used all around the world, but especially in Europe and theCommonwealth. U.S. transportation authorities rely heavily on the SN (also known as the Friction Number, or FN) for quantifying and monitoring friction data. Indirect standard measurement is how the SN is characterized in ASTME 274/E274M-15 (ASTM International, 2015).

Studies have revealed that accidents increase when friction levels (SFC or SN) onroadways are low. A minimum standard for pavement friction was set in 1966 after McCullough and Hankins analyzed 517 kilometers of rural Texas roadways. Kuttesch (2004) found that as SN decreased, the chance of an accident increased under wet circumstances, based on data from the Virginia Wet Accident Reduction Program. According to Vineret al. (2004), who conducted an analysis of the United Kingdom's skid resistance strategy, low SFC values lead to higher average collision rates over straight highway sections. According to research conducted by Cenek and Davies (2004) using SCRIM® data for New Zealand's State Highways, increasing the SFC by 0.1 would decrease the crash rate by 20% in dry circumstances and by 35% in wet ones.

The latest edition of "Pavement Friction Management," released in 2010, states that it is critical to gather pavement friction data at the network level and to identify high-risk sites for future investigation or action. In order to locate regions with low pavement friction, AASHTO suggests setting thresholds for investigation and action (AASHTO, 2008). In order to decide whether or not to intervene once the investigatory threshold has been crossed, a site inspection at the project level must be performed. Some transportation organizations, inspired by AASHTO's model, have set their own standards for study and action. Accident data, including collision history, field investigation, and route geometrics, are often analyzed with SN data throughout the whole transportation network by transportation agencies to determine what, if any, action to take. In Florida, for instance, a project-level investigation is conducted to determine if corrective actions are necessary if the friction number (FN40R; measured at 40 mph with a ribbed tire) is below 28 (for posted speeds less than 45 mph) or 30 (for posted speeds greater than 45 mph).

However, there is a dearth of research quantifying the BCR of developing investigation or intervention standards on a system-wide scale. The treatment cost or benefit of collision reduction was typically dependent on engineers' assessments, assumptions, or local experience, and the published study did not give a methodology for such calculations that would allow a transportation agency to duplicate the analysis. Over a 5-year period, the BCR for HFSTs put on horizontal bends on rural Texas highways was predicted by Brimley and Carlson (2012) to be anywhere from 20 to 60.

The purpose of this study is not to debate the relative merits of various maintenance strategies for reducing skid resistance or to settle the debate over whether or not the intervention threshold approach is the best option. Developing a model for skid resistance degradation (part a), evaluating the costs of skid resistance treatments (part b), and quantifying the savings in crash costs and other indirect expenses that result from improved skid resistance (part c) make up the methodology.

Figure 1 shows the overall design. Predicting the commencement of loss of traction by modeling the decrease in skid resistance is possible with a high degree of accuracy. In this study, we employ a Markov Chain (MC) model to estimate degradation due to its flexibility in incorporating both the available historical SN data and the established maintenance procedures. There are four key concepts in this paradigm: s states, p states, m states, and P and M degradation and maintenance transition probability matrices. Here, we'll have a more in-depth look at these ideas. In the first place, there is the idea of a certain current situation. S = s1, s2, ..., s_n represents the set of conditions that may be met in terms of SN, where r is the number of possible condition states. We followed the guidelines laid out by Thompson et al. (2002) when creating the condition states: each state should

1. Be Ranked From Best To Worst,
2. Be Adjacent,
3. Be Defined Using Existing State Highway Thresholds, Have Sufficient Observations For All The States Designated.

The u-condition vector is the alternative hypothesis. The percentage of the network is denoted by the vector u in each example. Condition states on a network can take the following forms: 20% in state 1, 15% in state 2, etc. The circumference of U equals R.

The last idea is the Negative Probability Matrix (P). The P matrix records the yearly probabilities that a certain section's SN will change from good to bad. Frequently, P looks like the matrix in Eq. (1) under typical conditions of deterioration. Values for pii indicate how likely it is that the SN will maintain its existing characteristics. From I through J, the integers pij show the likelihood that the SN will deteriorate. A lack of maintenance is to blame if a pavement's SN does not rise. When the pavement deterioration rate (prr) reaches 1, the pavement is in its worst SN condition and will continue in this state unless maintenance is performed. P also has the properties Pij = 1, 0 pij = 1, and r j = 1.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ 0 & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \qquad (1)$$

$$M = \begin{bmatrix} m_{11} & 0 & \cdots & 0 \\ m_{21} & m_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ m_{r1} & m_{r2} & \cdots & m_{rr} \end{bmatrix} \qquad (2)$$

The vector $\boldsymbol{u}$ and the matrices $\boldsymbol{P}$ and $\boldsymbol{M}$ 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.

$$\boldsymbol{u}_k = \boldsymbol{u}_0 * (\boldsymbol{P})^k \qquad (3)$$

Where:
$\boldsymbol{u}_k$ = Condition vector, year k.
$\boldsymbol{u}_0$ = Initial condition vector.
$\boldsymbol{P}$ = Deterioration Transition Probability Matrix.

$$\boldsymbol{u}_k = \boldsymbol{u}_0 * (\boldsymbol{M} * \boldsymbol{P})^k \qquad (4)$$

Where:
$\boldsymbol{u}_k$ = Condition vector, year k.

$$\hat{p}_{ij} = \frac{N_{i,j}}{\sum_{j=0}^{r} N_{i,j}} \qquad (5)$$

Where: $\hat{p}_{ij}$ = Estimated annual transition probability from condition state i to state j.
$N_{i,j}$ = Number of observed transitions from state i to state j.
$\sum_{j=0}^{r} N_{i,j}$ = 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 $\hat{\boldsymbol{P}}$ 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).

$$Min \sum_{k=1}^{4} \sum_{i=1}^{r} \frac{(\boldsymbol{u}_{i,k} - \hat{\boldsymbol{u}}_{i,k})^2}{\hat{\boldsymbol{u}}_{i,k}} \qquad (6)$$

$$\chi^2 = \sum_{i=1}^{r} \frac{(\boldsymbol{O}_i - \boldsymbol{E}_i)^2}{\boldsymbol{E}_i} \qquad (7)$$

Where:
$\boldsymbol{O}_i$ = Observed pavement sections in condition state i from the validation dataset.
$\boldsymbol{E}_i$ = Predicted pavement sections in condition state i from the validation dataset.
r = Total number of condition states.

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.

Its purpose is to see how accurate the forecast was. Based on P, the optimized matrix, Equation (3) predicts a future validation dataset size. After that, the Chi-Square (x2) statistic can be calculated with Equation (7). Developing a Budget Costs are assessed by taking into account three factors:

1. The Amount Of Money Required To Treat The Pavement Areas When Friction Levels Drop Below The Intervention Threshold;
2.The Value Of Lost Time Due To Treatments; And

3.The value of lost time due to safety risks in work zones. The number of lane miles of pavement that will need repairs is calculated using the degradation model. Estimate the annual lane-mile maintenance requirements.

Predicting the future state of the network requires the initial condition vector u0 as well as the matrices P and M, as indicated in Equation (4). The matrix M is calculated based on the therapy and the minimal SN level (the threshold at which action is taken). By definition of Eq. (4), treated pavements are assumed to degrade at the same rate as untreated pavements. In fact, for the first few years, treated pavements endured less deterioration than their untreated counterparts. Since anti-skid treatments don't last as long as the pavement, this estimate is on the low side, but it's still probably accurate. To estimate how many lane kilometers will need maintenance after projecting the network's future state, we apply Equation (8).

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

Where:
LM_k = Number of lane miles to be treated in year k.
$\sum_{i=1}^{r}$ = Sum over all the condition states.

Find out how much you may anticipate spending on upkeep. By calculating the total number of treated lane miles by the average cost of the treatment per lane mile, we can derive the annual maintenance expenses (Equation 5). The average treatment cost per lane mile across the network is depicted here.

$\sum_{j=1}^{i-1} m_{ij}$ = 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.

$$CO_k = LM_k * UCT \qquad (9)$$

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.

This paper solely estimates network-level travel delay costs, depreciation costs, and road safety costs because it is the only way to get an accurate picture of the BCR. Costs associated with Travel Delays and Decay These costs are related to the additional effort put in because of the delays caused by construction zones. The Federal Highway Administration's (FHWA) technique (FHWA, 2011) was used to estimate these costs.

The steps involved are outlined below.
(1) Average Travel Time Delay for Vehicles in Construction Zones: The delay includes not just the time it takes to get through the construction zone but also any time spent waiting at a stop sign or in a queue. The number of channels and the amount of traffic have an effect on some of these metrics (such as queue delay time). As a result, at the network level, we just look at how much longer it takes each car to get through the work zone. Costs of daily travel delays due to construction
(2) The cost is associated with the time of delay. The underlying idea is that the wasted hours may have been put to better use (FHWA, 2011).

II.ESTIMATING BENEFITS

The monetary value of accident reductions is the projected economic benefit. These accident reductions can be attained by treating pavement segments where friction levels are below the critical level. There are two different approaches to estimating crash avoidance. One strategy is to use a model to calculate the expected failure rate as a function of the SN. Crash rates for each condition state can be estimated, for instance, using a model in which collision rates per 100 million vehicle kilometers are a function of the SCRIM coefficient (Cenek and Davies, 2004). Alternatively, we can estimate accident rates for each circumstance. state by looking at past records.

This article estimates the accident rates per million vehicle miles traveled (VMT) for each condition state using available historical data. Calculate how many accidents have been avoided. By combining the predicted condition of the network (obtained from the MC model) with the projected accident rates per million VMT for each condition state (Ri) based on historical data or established models, an expected number of collisions may be calculated. If friction on the pavement is not increased, then the base case is the estimated number of crashes. If pavement friction is increased when pavement SN is at or below the critical value, the resulting number of crashes is the second scenario.

The probability matrix of transitions (P) was calculated in accordance with the Procedure. The degradation models were confirmed by a cross-validation of the P matrix, which produced p values of 0.89, 0.94, and 0.90 for the three cohorts, respectively. The validated P matrices for the three categories are displayed in Table 3. Forecasting the total annual mileage of roads that need maintenance.
The matrix M is built taking into account
(A) The Type Of Therapy Selected For The Analysis To Improve SN And
(B) The New SN Value Following Application Of The Treatment.

Preventive treatments such as seal coatings are examined in this study because of their prevalence on Austin District and TxDOT roads. Some seal coats are placed to increase the SN of the pavement to lessen the likelihood of accidents occurring in wet conditions (TxDOT, 2017). Seal coatings include laying down a single layer of aggregate and then covering it with a thin layer of bituminous material.

III.RESULTS

Highways take decades, urban freeways take years, and collectors and arterials take months. Here are the specifics of the three possible seal coat price points The estimated BCR for the life of the treatment was calculated under three different scenarios:
1.A Low-Cost Scenario Using The 25th Percentile Cost ($13,000 Per Lane Mile);
2. 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 shows the results when the three functional system groups are compared, while Figures 8–10 show the results when they are broken down by kind of road (Interstates, Urban Freeways, and Arterials and Collectors, respectively). Despite the fact that seal coat costs tend to change substantially, the data show that the BCR is quite constant. Interstate highways have a BCR between 24.5 and 22.0, with SN = 20 being the lowest limit. Even less variety is seen on metropolitan highways, arterials, and collectors.

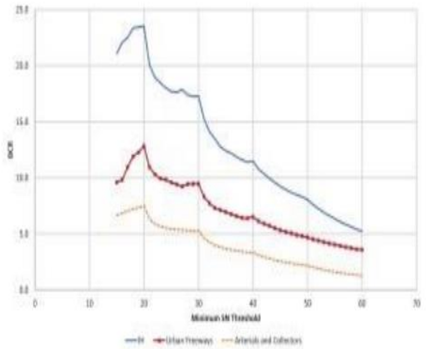

Figure 7: Benefit-Cost Ratio of Establishing a Minimum SN Threshold for Inter-state Highways, Urban Freeways and Arterials and Collectors, Using the Median Cost

These results suggest that as the minimum SN level is increased, the advantages (total crash reductions) are not enough to justify the rising maintenance costs. It should be highlighted, however, that a declining BCR is not necessarily evidence in favor of focusing repair efforts on the worst pavements. Findings should be taken with caution outside of a network in which the intervention threshold approach is being used to estimate the BCR, as that is the focus of this study.
In such a situation, transportation authorities must choose a happy medium between two feasible SN intervention thresholds:

1. one with a high BCR and low predicted overall crash reductions, and
2. one with a low BCR and high expected total crash reductions.

Similar estimates have been made 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 others. Wilson et al. (2016) found an average before-and-after BCR of 24.5 over a 5-year period for HFSTs applied on tight curves.

IV.CONCLUSIONS

The study's aim was to suggest a structure for evaluating the BCR and deciding on a cutoff for SN intervention. In the suggested method, an MC deterioration model was utilized to quantify the number of lanes and miles that needed to be addressed in order to determine the maintenance cost of the network. Travel delays and additional safety concerns due to construction zones added to the total cost. The value was determined by assigning a dollar amount to the expected crash reductions from the crash rates per VMT.

The study's conclusions are outlined below: The key objective of this research is to provide a methodology that transportation agencies can use as an analytical tool to evaluate the BCR of maintenance plans that aim to guarantee a minimal SN in a roadway network. This estimation is supposed to be replicable in many contexts, unlike previous research where the treatment cost or the benefit of accident reduction was based on an engineer's assessment, assumptions, or local experience. Even though the Austin District case study used treatment- and network specific data, the methodology is generalizable. It is crucial to have both a model of MC deterioration and a function that relates crash rates to pavement friction.

This research has the potential to improve not only SFC readings but also Skid values. For instance, a deterioration model like the one developed by Fulop et al. (2000) for SFC can be used to estimate treatment needs, and a model like the one developed by Cenek and Davies (2004), in which crash rates per 100 million vehicle kilometers are a function of SFC, can be used to estimate crash rates in each condition state.

The research's economic aspects can be adapted to local conditions as well. (2) Incorporating travel delay costs and safety expenses due to the presence of work zones strengthens the BCR framework developed. The BCR may now account for the costs incurred due to traffic jams. The purpose of this work is to provide an estimate of the BCR using the intervention threshold technique, in which only sections with friction levels below a specified threshold are handled by the agency. This means the findings are exclusive to systems where an agency uses an intervention threshold approach. The effectiveness of the intervention threshold strategy in preserving skid resistance is not assessed in this study. Additional research is needed to properly evaluate the cost-effectiveness of different maintenance processes and to compare different strategies seeking to regulate skid resistance at the network level.

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