Safety-oriented Pavement Performance Thresholds: Accounting for Unobserved Heterogeneity in a Multi-Objective Optimization and Goal Programming Approach

By

Panagiotis Ch. Anastasopoulos (Corresponding author)
Assistant Professor
Department of Civil, Structural and Environmental Engineering
Director, Engineering Statistics and Econometrics Application Research Laboratory
Associate Director, Institute for Sustainable Transportation and Logistics
University at Buffalo, The State University of New York
212 Ketter Hall
Buffalo, NY 14260
(716) 645-2114
panastas@buffalo.edu

Md Tawfiq Sarwar
Graduate Research Assistant
Department of Civil, Structural and Environmental Engineering
Engineering Statistics and Econometrics Application Research Laboratory
University at Buffalo, The State University of New York
204 Ketter Hall, Buffalo, NY 14260, USA
(765) 637-1883
mdtawfiq@buffalo.edu

And

Venky N. Shankar
Professor
Department of Civil and Environmental Engineering
Pennsylvania State University
University Park, PA 16802
(814) 865-9434
shankav@engr.psu.edu

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ABSTRACT

The cornerstone of transportation infrastructure asset management is managing the physical infrastructure, with pavement preservation being one of the most critical and costly assets. Preserving pavements in an appropriate manner extends their service life, and most importantly improves motorists’ safety and satisfaction while saving public tax dollars. To that end, this paper presents a methodology to estimate pavement performance thresholds that are cost-effective and safe for users. Using data from Indiana, the relationships of the three criteria, i.e., safety (accident rates), normalized treatment cost and pavement service life, with the pavement performance (roughness, rutting, overall rating, and surface deflection), road geometry, traffic characteristics and climate - are investigated and estimated. These relationships are utilized in a multi-objective optimization and goal-programming scheme to identify performance threshold values that trigger preservation treatments. These analytically determined threshold values are found to be comparable to historical thresholds and thresholds derived from experts’ and users’ opinions.

Keywords: Pavement performance thresholds; Pavement preservation; International roughness index; Rutting; Surface deflection; Pavement service life; Unobserved heterogeneity; Random parameters; Tobit regression; Hazard-based duration modeling; Multi-objective optimization; Goal programming.
1. INTRODUCTION

Pavement performance measures, quantitative or qualitative, reflect the extent to which specific pavement performance objectives are met. Performance thresholds are values of the performance measures that separate the desired pavement state (or service level) from the undesired one. Appropriate thresholds are a necessary condition of reaching the desired pavement performance goals and objectives. The selection of performance thresholds will also affect the service life of the pavement and the time when it needs to be treated.

There has been an abundance of past research investigating pavement performance thresholds and their determination. The 1998 Federal Highway Administration (FHWA) strategic plan (FHWA, 1999) defined a qualitative pavement condition term: pavement serviceability rating (PSR) and the approximate corresponding quantitative term is international roughness index (IRI). As an alternate to PSR, based on the proposal of US Army Corps of Engineers, the American Society for Testing and Materials (ASTM) defined Pavement Condition Rating (PCR). PCR is a 0 to 100 numerical index system where 0 indicates extremely poor pavement condition and 100 indicates excellent pavement condition. PCR is based upon visual inspection of pavement distress by qualified and trained engineers. Rutting depth (RUT) is another measure of pavement condition which is defined as a depression or groove worn into the pavement by the travel of wheels or by erosion from flowing water. Finally, pavement surface deflection (FWD) is another pavement condition indicator which is a measure of the magnitude and the shape of the deflection and is a function of pavement structure, traffic (both type and volume), temperature and other factors. Among the several pavement performance indicators, IRI, PCR, RUT and FWD are considered in this paper. The reasons for using these pavement performance indicators are: a) they represent various aspects of pavement deterioration with respect to safety and, b) it is not well understood
how the dimensions of rut depth, crack, deflection and roughness are individually responsible, especially in the context of their contributions to safety. Note that all of them are found to be significant in the analysis which clearly indicates that ignoring them would cause omitted variable bias in the models.

A number of studies used historical thresholds to develop design and preservation strategies or determine treatment effectiveness (Lamptey et al., 2005; Labi et al., 2005; Anastasopoulos et al., 2014; Warith et al., 2014, 2015). Other researchers have determined pavement performance thresholds based on users’ or experts’ opinion (Nair et al., 1985; Khattak et al., 1993; Ng et al., 1995; Kuemmel et al., 2001a, 2001b, 2001c; Shafizadeh et al., 2002; Shafizadeh and Mannering, 2003; Flintsch and Zaniewski, 1997). The FHWA (1999) recommended a threshold IRI value of 170 in/mi with respect to acceptable levels of road roughness by users. Shafizadeh and Mannering (2003) validated the FHWA’s acceptable levels of road roughness as 170 in/mi. Hicks et al., (2000) used the average thresholds for IRI, PCR and rut depth as 108.6 in/mi, 61.2 and 0.47 in, whereas, Lamptey et al., (2005) used as 113.1 in/mi, 88.3, and 0.19 in respectively. Labi et al., (2005) reported different historical threshold values of IRI, PCR and rutting depth for interstate and non-interstate roads. However, the thresholds presented in the literature are mostly historical thresholds, or are solely based on experts’ or users’ opinions, or some cost factors. This paper offers analytically determined threshold values by using advanced statistical models and mathematical programming while considering safety, budget and other constraints. The models are suggestive of the need to consider safety in the evaluation of pavement performance thresholds, a perspective that is missing in the extant literature. In summary, the goal of this paper is to shed some light on the management related aspects of the
various components of pavement deterioration with respect to not only budget and service life, but also to safety.

This paper develops a methodological framework for estimating specific safe and cost-effective threshold values with respect to pavement performance over time. Four pavement performance indicators are identified as crucial in determining trigger values for safety oriented pavement treatment initiation: the international roughness index (IRI), rutting, surface deflection, and pavement condition rating (PCR). The methodology is demonstrated using cost, pavement service life, and safety as the key threshold determinants, although other criteria can be easily accommodated in the proposed method.

2. STUDY FRAMEWORK

Provided that the measures of the pavement performance are appropriately determined (i.e., the performance indicators), the first step to identify the thresholds for each performance measure is to select well specified criteria. These may be utilized (in combination or not) to identify the threshold for each performance measure that initiates a pavement treatment. A starting point is to convert all performance criteria into directly comparable units, such as cost (user cost, operational cost, cost associated with environmental issues, etc.), or into dimensionless units. As such, the following three steps are proposed (Figure 1). These steps can be generalized for any type of infrastructure asset.

First, pavement performance measures are identified. Such performance measures are considered to be appropriate when they best state the pavement condition in measurable terms. The thresholds of these measures can then be approximated based on the set of predetermined pavement performance goals and identified criteria. Second, pavement performance criteria and
their relative importance are established. Example criteria considered for the approximation of the performance measure thresholds of a pavement treatment can be cost (preservation, operating, etc.), safety and security impacts, environmental and social impacts, or economic development. Finally, mathematical programming (multi-objective optimization and goal programming is used herein, as a possible approach; see Ragsdale, 2007) is used to approximate the pavement performance thresholds. As such, the decision variables are the pavement performance thresholds, the performance measures represent the objective functions, and the pavement performance criteria are the constraints.
3. METHODOLOGY

The proposed methodological framework is implemented to determine the performance thresholds that initiate pavement treatments for urban interstate flexible pavements in Indiana. Among the many indicators that measure the pavement performance, there are three that are typically used, roughness, pavement condition rating, and rut depth (Sarwar and Anastasopoulos, 2016). In this study, surface deflection was also considered.

Figure 1. Framework for pavement performance thresholds determination.
The IRI measures irregularities that can result from rutting, potholes, patching and other factors. In Indiana, the IRI is measured in inches/mile, with lower values indicating a smoother pavement (see Noyce and Bahia, 2005; Shafizadeh and Mannering 2003, 2006; Anastasopoulos et al., 2011).

Rut depth is defined as a depression worn into the pavement, in the longitudinal direction, by the traffic. It is measured as the differences in elevation on the pavement surface across the wheel path and is typically measured in inches. Excessive rutting can contribute to vehicle tracking and loss of control during maneuvering (Anastasopoulos et al., 2008).

The PCR is based upon visual inspection of pavement distress, as there is general agreement that the ability of a pavement to sustain traffic loads in a safe and efficient manner is adversely affected by the occurrence of observable distress. The PCR is expressed as an index ranging from 0 to 100 (100 being excellent pavement condition), which reflects the composite effects of varying distress types, severity, and extent upon the overall condition of the pavement.

Pavement surface deflection as measured by the falling-weight deflectometer (FWD) is used to evaluate the pavement structure. It is an important pavement evaluation tool because the magnitude and shape of pavement deflection is a function of pavement structure, traffic (type and volume), temperature and moisture affecting the pavement structure. The units for the surface deflection used in the analysis are thousandths of inches (or mils) from a FWD center-of-load deflection, corrected to a 9,000-pounds load applied on an 11.8-inch diameter plate, adjusted for temperature (65°F).

There exists abundant research in the literature that uses pavement performance indicators to reflect pavement condition. In fact, that is the purpose of these pavement performance indicators: to represent one or more aspects of the pavement condition by each indicator. For
example, the international roughness index (IRI) represents roughness of the pavement, rut depth represents the presence and depth of any rut or pothole, while surface deflection is used to evaluate the pavement structure. Pavement condition rating (PCR) provides an overall rating based on certain predetermined standards by ASTM. Several studies have used various pavement performance indicators to characterize the pavement condition, such as pavement serviceability (Prozzi and Madanat, 2004; Bianchini and Bandini, 2010; Pan et al., 2011); pavement roughness (Smith et al., 1997; Hicks et al., 1997; Puccinelli and Jackson, 2007; Anastasopoulos, 2009; Hong and Prozzi, 2010; Anastasopoulos et al., 2012c), rutting depth (Hicks et al., 1997; Archilla 2006; Puccinelli and Jackson, 2007; Anastasopoulos, 2009), pavement condition rating (Chan et al., 1997; Anastasopoulos, 2009), measure of pavement fatigue (Madanat et al., 1997; Puccinelli and Jackson, 2007) and individual and composite pavement condition indexes (Butt et al., 1987; Jackson et al., 1996). Pavement condition is one of the influential factors associated with accident occurrence and injury-severity (Mannering et al., 2016). Particular mention of pavement condition measures’ effects on accident occurrence, accident rates and injury severity is provided in have varying effects on accident occurrence, rates or injury-severities (Mayora and Piña, 2009; Anastasopoulos et al., 2012a, 2012b; Li et al., 2013; Pulugurtha et al., 2013; Buddhavarapu et al., 2013; Dong et al., 2015). These studies address pavement roughness, surface deflection, rutting depth, pavement condition rating.

All four indicators are assumed to be representative of the condition of the pavement. Therefore, the objective is to obtain the optimal values of the IRI, rut depth, PCR, and surface deflection that minimize accidents and treatment costs, and maximizes the pavement service life, subject to safety, budget constraints, and other criteria. Note that estimated values for dependent variables are used instead of observed values, due to data limitations (i.e., some roadway segments.
did not have information for one or more of the objectives), and to simplify the right-hand side
problem (i.e., introduce the variables linearly on the right-hand side, while incorporating on the
left-hand side the nonlinearity of the variable effects via random parameters statistical modeling
estimation). The following sections present the establishment of the relationships (through random
parameters statistical modeling) between historical pavement performance thresholds, and
treatment cost, pavement service life, and safety (accident rates).

3.1. Data Description

Pavement and roadway data were collected from the Indiana Department of Transportation
(INDOT) pavement condition and pavement management databases, and from INDIPAVE, a
database consisting of data on pavement condition, weather, pavement structure, traffic,
maintenance, and other information for over 10,000, one-mile pavement sections in Indiana.
Accident data were gathered from the Fatality Analysis Reporting System (FARS), and from
Indiana Police Accident Reports (from the National Highway Traffic Safety Administration –
NHTSA database). Weather information was collected from the Indiana State Climate Office.
The data include information for 1,254 urban interstate road sections in Indiana from 1999 to 2007
– such as information on pavement drainage, traffic volume, pavement preservation cost, weather,
pavement condition (IRI, PCR, rut depth and surface deflection), road geometry, and accident-
specific information. The pavement data are available for each year of the analysis period;
however, the accident related data are available in an aggregated fashion for the analysis period.
The roadway data are divided into fixed-length roadway sections of one mile each defined by
roadway geometrics and pavement type. The section defining information includes shoulder,
pavement and median characteristics, number of lanes and speed limit. For an analytical
description of the data, interested readers are referred to Anastasopoulos (2009). Table 1 provides descriptive statistics of key variables.

Table 1. Summary statistics of selected variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean or %</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed threshold value for international roughness index (IRI) (in/mi)</td>
<td>125.30</td>
<td>31.12</td>
</tr>
<tr>
<td>Observed threshold value for pavement condition rating (PCR) (scale of 0-100)</td>
<td>60.28</td>
<td>8.99</td>
</tr>
<tr>
<td>Observed threshold value for rut depth (in)</td>
<td>0.22</td>
<td>0.16</td>
</tr>
<tr>
<td>Observed threshold value for surface deflection (mils)</td>
<td>15.98</td>
<td>5.43</td>
</tr>
<tr>
<td>Base IRI after rehabilitation (in/mi)</td>
<td>69.65</td>
<td>30.88</td>
</tr>
<tr>
<td>Base PCR after rehabilitation (scale of 0-100)</td>
<td>96.45</td>
<td>2.84</td>
</tr>
<tr>
<td>Base rut depth after rehabilitation (in)</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Base surface deflection after rehabilitation (mils)</td>
<td>2.73</td>
<td>1.56</td>
</tr>
<tr>
<td>Average (over the 9-year period) IRI (in/mi)</td>
<td>102.72</td>
<td>32.48</td>
</tr>
<tr>
<td>Average (over the 9-year period) PCR (scale of 0-100)</td>
<td>88.79</td>
<td>3.88</td>
</tr>
<tr>
<td>Average (over the 9-year period) rut depth (in)</td>
<td>0.15</td>
<td>0.06</td>
</tr>
<tr>
<td>Average (over the 9-year period) surface deflection (mils)</td>
<td>8.51</td>
<td>4.49</td>
</tr>
<tr>
<td>Accident rates (number of accidents over 100 million VMT)</td>
<td>68.09</td>
<td>143.67</td>
</tr>
<tr>
<td>Service life of the pavement (years)</td>
<td>13.52</td>
<td>3.26</td>
</tr>
<tr>
<td>Average annual daily traffic - AADT (veh/day)</td>
<td>29,593.55</td>
<td>27,504.91</td>
</tr>
<tr>
<td>AADT indicator (1 if AADT less than 4,000 veh/day, 0 otherwise)</td>
<td>41%</td>
<td></td>
</tr>
<tr>
<td>Cumulative (over treatment study period) daily no. of trucks (in 1000s)</td>
<td>38.15</td>
<td>23.94</td>
</tr>
<tr>
<td>Cumulative (over treatment study period) daily no. of passenger cars (in 1000s)</td>
<td>169.86</td>
<td>131.44</td>
</tr>
<tr>
<td>Horizontal curve indicator (1 if present, 0 otherwise)</td>
<td>49%</td>
<td></td>
</tr>
<tr>
<td>Median indicator (1 if no barrier and no median present, 0 otherwise)</td>
<td>24%</td>
<td></td>
</tr>
<tr>
<td>Treatment contract cost per lane-mile (million USD)</td>
<td>253,904</td>
<td>503,653</td>
</tr>
<tr>
<td>Average treatment cost per lane-mile per year over treatment period (USD)</td>
<td>66,118.19</td>
<td>55,001.59</td>
</tr>
<tr>
<td>Treatment contract cost per lane-mile indicator (less than 50,000USD)</td>
<td>46.68%</td>
<td></td>
</tr>
<tr>
<td>Average annual range of temperature (°F) over treatment period</td>
<td>24.09</td>
<td>11.34</td>
</tr>
<tr>
<td>Average annual precipitation over the treatment period (inches)</td>
<td>1.53</td>
<td>0.31</td>
</tr>
<tr>
<td>Drainage class indicator: somewhat poorly, poorly, or very poorly drained</td>
<td>54.57%</td>
<td></td>
</tr>
<tr>
<td>Drainage class indicator: poorly or very poorly drained</td>
<td>20.78%</td>
<td></td>
</tr>
</tbody>
</table>

With respect to estimation issues, the cumulative daily number of trucks \( (T_n) \) over the treatment study period \( n \), is estimated as:

\[
T_n = \sum_{i=1}^{n} TRUCKS = 365 \cdot \sum_{i=1}^{n} AADT_i \cdot CT_i, \tag{1}
\]
where, $AADT_i$ is the average annual daily traffic for year $i$, and $CT_i$ is the percentage of commercial trucks for the same year $i$. Also, all monetary amounts are converted and expressed in 2007 USD prices (1987 base), using the Price Trends for Federal-Aid Highway Construction:

$$M^* = M_{ref} \times \frac{I^*}{I_{ref}},$$  \hspace{1cm} (2)

where, $M^*$ is the monetary cost in any year, $M_{ref}$ the monetary cost in a reference year, $I^*$ the price index for the year of the $M^*$, and $I_{ref}$ the price index for the reference year.

Finally, a methodological concern that needs to be accounted for is the potential varying effect of the parameters across the observations due to unobserved heterogeneity. One possible way to address this, is by allowing the effect of the estimable parameters to vary across the observations through the use of random parameters, which have been shown to reduce parameter bias and inconsistency (Mannering et al., 2016; Washington et al., 2011; Anastasopoulos and Mannering, 2009, 2011, 2016; Anastasopoulos et al., 2012a; Benhood et al., 2014; Mannering and Bhat, 2014; Russo et al., 2014; Yasmin et al., 2014, 2015; Barua et al., 2015, 2016; Benhood and Mannering, 2015; Eluru and Yasmin, 2015; Sarwar et al., 2016). To that end, the estimable parameters are written as,

$$\beta_i = \beta + u_i,$$  \hspace{1cm} (3)

where, $\beta_i$ is a vector of estimable parameters, and $u_i$ a randomly distributed term (i.e., normally distributed with mean zero and variance $\sigma^2$). For model estimation, a simulated maximum likelihood approach is used. To improve estimation efficiency, 200 Halton draws are utilized (Washington et al., 2011; Halton, 1960; Bhat, 2003; Train, 1999).
3.2. Treatment Cost Modeling

A random parameters non-linear regression model is initially estimated to establish relationships between average treatment costs per lane-mile per year (a normalized treatment cost so that all treatment contracts can be cost-comparable), and pavement performance thresholds, traffic loads, and other factors. Note that the non-linear model was preferred over the linear so as to restrict the treatment cost to positive values. If a linear relationship were utilized, the model would predict non-realistic negative treatment cost values.

Table 2 presents the model estimation results (with all parameter signs being intuitive). The resulting relationship between the average treatment costs per lane-mile per year, $\overline{C}$, and the independent variables is:

$$\overline{C} = e^{(IRI_t, PCR_t, RUT_t, FWD_t, T_c, PC_t)}$$

where, $IRI_t$, $PCR_t$, $RUT_t$, and $FWD_t$ are the historical/observed threshold values of the international roughness index, pavement condition rating, rut depth, and surface deflection, respectively, and $T_c$ and $PC_t$ are the cumulative, over the treatment study period, daily number of trucks and passenger cars, respectively. Note that the constant is found to be a random parameter with a mean of 9.439 and standard deviation of 9.276, which implies that the value of the constant (or intercept) varies across observations. This indicates a strong random effect due to unobserved heterogeneity that cannot be attributed to the variables included in the model.
Table 2. Random parameters regression model estimation results for the natural logarithm of the average treatment contract cost per lane-mile per year over the treatment period

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>9.439</td>
<td>7.68</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Standard deviation of parameter density function</td>
<td>9.276</td>
<td>5.50</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for international roughness index (IRI) (in/mi)</td>
<td>0.021</td>
<td>7.61</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for pavement condition rating (PCR) (scale of 0-100)</td>
<td>-0.002</td>
<td>-4.85</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for rut depth (in)</td>
<td>0.163</td>
<td>6.65</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for surface deflection (mils)</td>
<td>0.165</td>
<td>4.35</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Cumulative (over treatment study period) daily no. of trucks (in 1000s)</td>
<td>0.021</td>
<td>5.11</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Cumulative (over treatment study period) daily no. of passenger cars (in 1000s)</td>
<td>0.010</td>
<td>5.34</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

$R^2$ 0.73  
Adjusted $R^2$ 0.71  
$N$ 1,254

3.3. Pavement Service Life Modeling

For pavement survival data, hazard-based models can be used to study the conditional probability of the pavement service life ending at some time $t$, given that it has not ended until time $t$ (see for example, Sathyanarayanan et al 2008; Anastasopoulos, 2009; Sathyanarayanan and Shankar 2012; Anastasopoulos and Mannering, 2014). This conditional probability is important because it will likely increase significantly as the pavement service life increases. To formulate an estimable model, the hazard function is written as (see Washington et al., 2011):

$$h(t) = g(t)/[1 - G(t)]$$ (5)

where $G(t)$ and $g(t)$ are the cumulative distribution and density functions of pavement service lives, respectively. This hazard function gives the rate at which the pavement service lives are ending at time $t$, given that they have lasted up to time $t$. If this hazard function is upward sloping as time passes ($dh(t)/dt > 0$), it means that the conditional probability that the pavement service life will end soon (given that it has not ended so far) increases as the pavement lasts longer. If the hazard
function is $dh(t)/d(t)<0$, then that conditional probability decreases as the pavement lasts longer; the likelihood of failure decreases as the pavement lasts longer. Finally, if the hazard function is constant as time passes ($dh(t)/d(t)=0$), then the service life ending probability is independent of the length of time the pavement has lasted.

A hazard-based model can therefore be estimated as:

$$ h_s(t | X) = h_0(t) e^{(-\beta X_n)}, $$ (6)

where, $X_n$ is a vector of explanatory variables, $\beta$ is a vector of estimable parameters, and $h_0(t)$ is the baseline hazard that denotes the hazard when all elements of the explanatory variables vector are zero. In estimating Equation (6), a common approach is to consider various parametric forms of the underlying hazard function (Prozzi and Madanat, 2000; Wang et al., 2005; Yu, 2005; Yang 2007). This study tested the most widely used parametric forms (exponential, Weibull, log-logistic, and Weibull with Gamma heterogeneity models), and the random parameters Weibull model was found to provide the best overall statistical fit. The Weibull model allows monotonically increasing or decreasing hazard functions, implying the probability of a pavement service life ending can increase or decrease the longer the pavement lasts.

Table 3 presents the pavement service life model estimation results (with all parameter signs being intuitive). The resulting relationship between the pavement service life, $S_t$, and the independent variables is:

$$ S_t = a^{(IRI_b, PCR_b, RUT_b, FWD_b, IRI, PCR, RUT, FWD, T, D_p, F, R, C)} $$ (7)

where, $IRI_b$, $PCR_b$, $RUT_b$, and $FWD_b$ are the historical/observed base values (pavement performance the year after a rehabilitation treatment occurred) of the international roughness index, pavement condition rating, rut depth, and surface deflection, respectively, $D_p$ a drainage class indicator variable representing poorly or very poorly drained pavements, $F$ the average
annual range of temperature over the treatment period, $\bar{R}$ the average annual precipitation over the treatment period, $C$, an indicator variable representing low treatment contract cost per lane-mile (less than 50,000 USD), and the rest of the variables as previously defined. Note that “poorly” or “very poorly drained” class and treatment contract cost per lane mile (less than 50,000 US dollars) are found to be random parameters. For example, the dummy variable namely, treatment contract cost per lane mile (less than 50,000 US dollars) has a mean of -0.021 and a standard deviation of 0.024, which implies that in 81% of the observations, a treatment contract cost of less than 50,000 US dollars per lane-mile would decrease pavement service life; but, for 19% of the observations, it would increase the service life – which reflects the presence of heterogeneity in the data. This indicates that in certain instances, due to unique climatic and traffic volume effects, low cost approaches can serve as productive counter measures for extending pavement service life.

### 3.4. Safety Modeling

Highway safety has been thoroughly approximated from an accident frequency approach (Shankar et al., 1995, 1997, 1998; Poch and Mannering, 1996; Hadi et al., 1995; Abdel-Aty and Radwan, 2000; Joshua and Graber, 1990; Savolainen and Tarko, 2005; Anastasopoulos and Mannering, 2009; Bhat et al., 2014; Chiou et al., 2014; Mohammadi et al., 2014; Venkataraman et al., 2014; Chiou and Fu, 2015; Coruh at al., 2015; Zou et al., 2014, 2015). The significance of the traditional methods on accident frequencies is well-established. However, the usage of accidents per vehicle-miles traveled (VMT) gives a more normalized prediction of highway safety, permitting more accurate time or temporal comparisons, or both (Anastasopoulos et al., 2008; Anastasopoulos et al., 2012a; Anastasopoulos et al., 2012b; Anastasopoulos, 2016).
From the perspective of statistical modeling, accidents per VMT is a continuous variable. However, because of accident rates on specific highway sections are assessed over some finite time period, there is the likelihood that many highway sections will have no accidents reported during the analysis period. The solution to this is to consider accident rates as a censored (at zero) dependent variable and apply tobit regression analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.630</td>
<td>15.70</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Base international roughness index (IRI) after rehabilitation (in/mi)</td>
<td>-0.003</td>
<td>-5.70</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Base pavement condition rating (PCR) after rehabilitation (scale of 0-100)</td>
<td>0.009</td>
<td>6.37</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Base rut depth after rehabilitation (in)</td>
<td>-2.210</td>
<td>-21.59</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Base surface deflection after rehabilitation (mils)</td>
<td>-0.039</td>
<td>-4.45</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for international roughness index (IRI) (in/mi)</td>
<td>0.001</td>
<td>4.77</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for pavement condition rating (PCR) (scale of 0-100)</td>
<td>-0.003</td>
<td>-3.94</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for rut depth (in)</td>
<td>1.464</td>
<td>6.96</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Observed threshold value for surface deflection (mils)</td>
<td>0.052</td>
<td>6.43</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Cumulative (over treatment study period) daily no. of trucks (in 1000s)</td>
<td>-0.010</td>
<td>-4.05</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Drainage class: poorly or very poorly drained</td>
<td>-0.116</td>
<td>-5.79</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Standard deviation of parameter density function</td>
<td>0.144</td>
<td>4.67</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Average annual range of temperature (°F) over treatment period</td>
<td>-0.003</td>
<td>-4.06</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Average annual precipitation over the treatment period (in)</td>
<td>-0.095</td>
<td>-5.06</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Treatment contract cost per lane-mile (less than 50,000USD)</td>
<td>-0.021</td>
<td>-4.09</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Standard deviation of parameter density function</td>
<td>0.024</td>
<td>6.77</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>P</td>
<td>6.2109</td>
<td>18.7666</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>LL(0)</td>
<td>-279.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LL(β)</td>
<td>-47.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>McFadden Pseudo $R^2$</td>
<td>0.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1,254</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
When a tobit regression model is estimated it is found that accident rates are associated with each of the four pavement performance thresholds. The accident rate (number of accidents per 100-million VMT) is calculated as (Anastasopoulos et al., 2008):

\[
\text{Accident Rate}_i = \frac{\sum_{n \text{Year}=1}^{n} \text{Accidents}_{\text{Year},i} \times \sum_{n \text{Year}=1}^{n} \text{AADT}_{\text{Year},i} \times L_i \times 365}{100,000,000}
\]  

(8)

where, \( \text{Accident Rate}_i \) is the number of accidents per 100-million VMT on roadway section \( i \), \( \text{Year} \) denotes the year (from 1 to \( n \)), \( \text{Accidents}_{\text{Year},i} \) is the number of accidents in the \( n \)th year on the \( i \)th roadway section, \( \text{AADT}_{\text{Year},i} \) the average annual daily traffic in the \( n \)th year on the \( i \)th roadway section, and \( L_i \) the length of roadway section \( i \).

The accident rates for the nine-year period (1999-2007) for each road section are defined using Equation (8). The time-varying parameters, such as pavement performance and traffic variables, are averaged over the analysis period. Note that a large number of road sections (approximately 40 percent of the observations) were found to have no accidents throughout the analysis period. In such cases, tobit regression is appropriate (see Anastasopoulos et al., 2008).

The tobit model (Tobin, 1958) is used for the safety analysis, as the accident-rate data considered herein are left-censored with a clustering at zero (because accidents may not be observed on all roadway sections during the period of observation). For a roadway section \( i \), a limit of zero is used, and:

\[
Y_i^* = \beta X_i + \epsilon_i, \quad i = 1, 2, \ldots, N,
\]

\[
Y_i = \begin{cases} 
Y_i^* & \text{if } Y_i^* > 0 \\
0 & \text{if } Y_i^* \leq 0,
\end{cases}
\]

(9)

where, \( N \) is the number of observations, \( Y_i \) is the number of accidents per 100-million vehicle miles traveled, \( X_i \) is a vector of independent variables (pavement condition, traffic and roadway section...
characteristics), $\beta$ is a vector of estimable parameters, and $\varepsilon_i$ is a normally and independently distributed error term with zero mean and constant variance $\sigma^2$. It is assumed that there is an implicit, stochastic index (latent variable) equal to $Y^*_i$ which is observed only when positive.

The expected value of the dependent variable for all cases, $E[Y]$, is (removing the subscript $i$ to simplify the exposition):

$$E[Y] = \beta X F(z) + \sigma f(z), \quad (10)$$

where, $z = \beta X / \sigma$ is the $z$-score for an area under the normal curve, $F(z)$ is the cumulative normal distribution function associated with the proportion of cases above the zero, $f(z)$ the unit normal density, and $\sigma$ the standard deviation of the error term. The relationship among the expected value of all observations, $E[Y]$, the expected value for cases above zero, $E[Y']$, and the probability of being above zero, $F(z)$ is:

$$E[Y] = F(z)E[Y'] \quad (11)$$

where, $Y'$ denotes observations above zero in the accident-rate case.

Table 4 presents the random parameters model estimation results (with all parameter signs being intuitive).

The resulting relationship between the accident rates, $A_r$, and the independent variables is:

$$A_r = f(\text{IRI}, \text{PCR}, \text{RUT}, \text{FWD}, \text{HC}, \text{M}, \text{AADT}) \quad (12)$$

where, $\text{HC}$, $\text{M}$, and $\text{AADT}$ are indicator variables representing horizontal curve presence, median or median barrier absence, and low (less than 4,000 vehicles/day) average annual daily traffic, respectively. The remaining variables are as previously defined. Note that the horizontal curve indicator and the median indicator variables are found to be statistically significant random parameters. With a mean of 23.222 and standard deviation of 17.646, the presence of horizontal curve increases the accident rate in 91% of the observations; but in 9% of the observations, the
accident rate decreases. This indicates that the presence of horizontal curve on a roadway segment in and of itself does not always indicate a counter-productive effect on safety. There may be design instances where the curve presence is a strong deterrent to risky driving that drivers slow their approach and departure speeds on the curve to avoid accidents. In terms of sensitivity, for example, if horizontal curve is present, it increases the number of accidents per 100-million VMT by 10.91 and increases the probability of having a 100-million VMT accident rate above zero by 19.36%. Among the pavement related variables, an increase in the observed threshold value of IRI, rut depth, and surface deflection is found to increase accident rate, while, an increase in the observed threshold value of PCR is found to decrease accident rate. For example, a one mils (unit for surface deflection: thousandths of inches) increase in the observed threshold value of surface deflection, increases the number of accidents per 100-million VMT by 3.69 and increases the probability of having a 100-million VMT accident rate above zero by 6.55%. Similarly, a one unit respective increase of IRI and rut depth, increases the number of accidents per 100-million VMT by 0.61 and 216.80, respectively. The corresponding increase in the probability of having a 100-million VMT accident rate above zero is 1.08% and 384.63%, respectively. On the other hand, a one unit increase of PCR decreases the number of accidents per 100-million VMT by 1.25, and increases the probability of having a 100-million VMT accident rate above zero by 2.22%.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-stat</th>
<th>p-value</th>
<th>Overall Sensitivity</th>
<th>Zero Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed threshold value for international roughness index (IRI) (in/mi)</td>
<td>1.301</td>
<td>4.59</td>
<td>&lt;0.001</td>
<td>0.61</td>
<td>1.08%</td>
</tr>
<tr>
<td>Observed threshold value for pavement condition rating (PCR) (scale of 0-100)</td>
<td>-2.665</td>
<td>-20.76</td>
<td>&lt;0.001</td>
<td>-1.25</td>
<td>-2.22%</td>
</tr>
<tr>
<td>Observed threshold value for rut depth (in)</td>
<td>461.444</td>
<td>4.73</td>
<td>&lt;0.001</td>
<td>216.80</td>
<td>384.63%</td>
</tr>
<tr>
<td>Observed threshold value for surface deflection (mils)</td>
<td>7.859</td>
<td>2.15</td>
<td>0.032</td>
<td>3.69</td>
<td>6.55%</td>
</tr>
<tr>
<td>Horizontal curve indicator variable (1 if present, 0 otherwise)</td>
<td>23.222</td>
<td>2.62</td>
<td>0.009</td>
<td>10.91</td>
<td>19.36%</td>
</tr>
<tr>
<td>Standard deviation of parameter density function</td>
<td>17.646</td>
<td>3.29</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median indicator variable (1 if no barrier and no median present, 0 otherwise)</td>
<td>24.406</td>
<td>3.15</td>
<td>0.002</td>
<td>11.47</td>
<td>20.34%</td>
</tr>
<tr>
<td>Standard deviation of parameter density function</td>
<td>15.092</td>
<td>1.86</td>
<td>0.063</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AADT indicator variable (1 if AADT less than 4,000 veh/day, 0 otherwise)</td>
<td>15.162</td>
<td>2.09</td>
<td>0.037</td>
<td>6.42</td>
<td>11.39%</td>
</tr>
<tr>
<td>Sigma</td>
<td>47.124</td>
<td>18.23</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LL(0)</td>
<td>-1234.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LL(β)</td>
<td>-700.44</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maddala Pseudo $R^2$</td>
<td>0.99</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>1.254</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Overall Sensitivity refers to the change in the overall expected value $\frac{\partial E[Y]}{\partial X_k}$, whereas, Zero Sensitivity refers to the percent change in the cumulative probability of being above zero (see Anastasopoulos et al., 2008, 2012b).

### 3.5. Safety Criterion

The accident rate of each road section is compared to the typical accident rate (i.e., safety norm) for the set $\sigma$ of all the sections. The typical accident rate or safety norm ($SN_\sigma$) can be estimated as:

$$SN_\sigma = \frac{\sum_{i} \sum_{\sigma} Accidents_i}{\left( \sum_{i} \sum_{\sigma} AADT_i \times L_i \times 365 \right) / 100,000,000}$$

(13)
where $\text{Accidents}_i$ is the number of accidents on roadway section $i$, $\text{AADT}_i$ the average annual daily traffic in roadway section $i$, and $L_i$ the length of roadway section $i$.

From this comparison, the road sections are ranked from the section with the lowest accident-rate to safety-norm ratio, to the section with the highest. The accident rate value of the 85th percentile (note that zeros, which implies road sections without accidents during the analysis period, are included in the determination of the percentiles) of road sections where the safety norm is exceeded at most is the safety constraint. To approximate a range of the thresholds, the 80th and 90th percentiles can also be used. The $P$th percentile of $N$ ordered values can be obtained by first calculating the rank (Washington et al., 2011):

$$n = \frac{1}{100} \cdot N \cdot P + \frac{1}{2},$$  \hfill (14)

which can then be rounded to the nearest integer, and the value that corresponds to that rank can be approximated. As such, the 80th, 85th, and 90th percentiles of the accident rates are 55.4, 75.9, and 88.4, respectively.

Using multi objective optimization and goal programming, a set of optimal performance thresholds with respect to the 80th, 85th, and 90th percentiles (other percentiles and constraints may also be used) of the most hazardous road sections can be approximated. Much of the extant literature regarding mathematical programming applications to pavement rehabilitation has focused on timing of resurfacing or rehabilitation activities (see for example, Ouyang and Madanat 2004, 2006; Anastasopoulos et al., 2014). The notion of determining optimal thresholds based on a contemporaneous performance measure such as safety, has not been addressed in the literature, to the authors’ knowledge.
4. PAVEMENT PERFORMANCE THRESHOLD ESTIMATION

Following the process described earlier (Figure 1), one must first solve the problem for each of the identified objectives to determine the optimal value of each objective (solve the problem to find the solution that optimizes the first objective and use this optimal value as a reasonable/target value, then solve the problem for the second objective and use its optimal value as a reasonable/target value, and so on). The three objective functions used (more can be used, as needed) to estimate the pavement performance thresholds are:

Minimize treatment cost, \( \bar{C} : f_1(X_1, X_2, \ldots, X_n) \rightarrow \min \) (15)

Maximize pavement service life, \( S_i : f_2(X_1, X_2, \ldots, X_n) \rightarrow \max \) (16)

Minimize accident rates, \( A_R : f_3(X_1, X_2, \ldots, X_n) \rightarrow \min \) (17)

Subject to:

Safety constraint: \( f_\alpha(X_1, X_2, \ldots, X_n) \rightarrow c_\alpha \) (18)

Budgetary constraint: \( f_\beta(X_1, X_2, \ldots, X_n) \rightarrow c_\beta \) (19)

Other constraints: \( f_\mu(X_1, X_2, \ldots, X_n) \rightarrow c_\mu \) (20)

where, \( X_1, X_2, \ldots, X_n \) are the decision (\( IRI_t, PCR_t, RUT_t, \) and \( FWD_t \)) and other independent variables, \( f_1, f_2, \ldots, f_n \) the objective functions (herein, Equations 4, 7, and 12, respectively), and \( f_\alpha, f_\beta, \ldots, f_\mu \) and \( c_\alpha, c_\beta, \ldots, c_\mu \) constraints and constraint values, respectively. For example, for the safety constraint, the 80th, 85th, and 90th percentiles of the accident rates used (\( SN_\sigma \)), are 55.4, 75.9, and 88.4, respectively; other constraints involve budget restrictions, and extreme values of the independent variables from the Equations 4, 7, and 12.

Next, the objectives are restated as goals (a constraint with a flexible, or ‘soft’ right-hand side value also called target value) using the optimal objective values identified in the previous
A deviation function is also created for each goal that measures the amount by which any given solution fails to meet the goal (as an absolute or a percentage). As deviation function for any goal $i$:

$$d^\pm_i = \frac{\tau_i - t_i}{t_i},$$  \hspace{1cm} (21)$$

and with Equation 21, the weighted sum of the percentage deviations is:

$$\sum_i \frac{1}{t_i}(w^-_i d^-_i + w^+_i d^+_i),$$  \hspace{1cm} (22)$$

where, $\tau_i$ and $t_i$ are the actual and target values for goal $i$, respectively, $w^-_i$, numeric constants that can be assigned values to weight the deviational variables, and $d^\pm_i$ deviational variables that represent the amount by which each goal deviates from its target values.

For each of the deviation functions, we assign a weight and create a constraint that requires the value of the weighted deviation function to be less than the minimax variable $\Omega$:

$$\Omega = \text{MAX} \left[ \left( \frac{1}{t_1} (w^-_1 d^-_1 + w^+_1 d^+_1) \right), \left( \frac{1}{t_2} (w^-_2 d^-_2 + w^+_2 d^+_2) \right), \ldots, \left( \frac{1}{t_i} (w^-_i d^-_i + w^+_i d^+_i) \right) \right].$$  \hspace{1cm} (23)$$

We then solve the resulting problem with the objective of minimizing $\Omega$ (note that if the solution is not acceptable, then the weights need to be re-adjusted):

Minimize the minimax variable: $\Omega \rightarrow \text{min}$  \hspace{1cm} (24)$$

Subject to:

$$\left( \frac{1}{t_1} (w^-_1 d^-_1 + w^+_1 d^+_1) \right) \leq \Omega$$  \hspace{1cm} (25)$$

$$\left( \frac{1}{t_2} (w^-_2 d^-_2 + w^+_2 d^+_2) \right) \leq \Omega$$  \hspace{1cm} (26)$$
\[ \frac{1}{t_i}(w_i d_i^- + w_i d_i^+) \leq \Omega \]  

(27)

\[ d_i^- \leq \Omega \]  

(28)

\[ d_i^+ \leq \Omega \]  

(29)

\[ d_i^- \leq \Omega \]  

(30)

\[ d_i^+ \leq \Omega \]  

(31)

where, \( \Theta_i \) is the weighted percentage deviation from the target values for the goals, and \( \Omega \) the minimax objective function.

Thus, as \( \Omega \) is minimized, the weighted percentage deviation from the target values for each of the four goals is also minimized. This way, the maximum weighted deviation from any of the goals is minimized (or the maximum deviation is minimized). Note that we set \( w_i = 1 \), as it is assumed that all the objectives are of the same importance.

4.1. Discussion of Results and Comparison with Literature Thresholds

The solution obtained for this problem gives a set of pavement performance threshold values that is the closest to the target values. With respect to the independent variables, three scenarios are explored (all safety oriented):

Scenario 1: Independent variables take relatively minimum values (which correspond to a lower accident rate state);

Scenario 2: Independent variables take median values (which correspond to a medium accident rate state; and

...
Scenario 3: Independent variables take relatively maximum values (which correspond to a higher accident rate state).

Table 5 presents the estimated pavement performance thresholds for the three scenarios for the 80th, 85th, and 90th percentile of accident rates.

Table 5. Estimated pavement performance thresholds for different scenarios

<table>
<thead>
<tr>
<th>Pavement Condition Indicators</th>
<th>Scenario 1</th>
<th></th>
<th>Scenario 2</th>
<th></th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>80th</td>
<td>85th</td>
<td>90th</td>
<td>80th</td>
<td>85th</td>
</tr>
<tr>
<td>IRI (in/mi)</td>
<td>177.9</td>
<td>205.1</td>
<td>228.2</td>
<td>148.7</td>
<td>189.3</td>
</tr>
<tr>
<td>PCR (0-100)</td>
<td>54.8</td>
<td>40.4</td>
<td>30.2</td>
<td>64.8</td>
<td>53.0</td>
</tr>
<tr>
<td>Rut depth (in)</td>
<td>0.31</td>
<td>0.38</td>
<td>0.42</td>
<td>0.38</td>
<td>0.44</td>
</tr>
<tr>
<td>Surface deflection (mils)</td>
<td>20.7</td>
<td>25.8</td>
<td>29.0</td>
<td>15.3</td>
<td>21.5</td>
</tr>
</tbody>
</table>

Note that in Scenario 1, the independent variables take minimum values and this results in less hazardous road sections. Similarly, in Scenario 3, the independent variables take maximum values resulting in more hazardous road sections. In words, if the effect of independent variables with negative effects (with negative signs) on accident rates is minimized (or maximized), this will in fact result in higher (or lower) accident rates. Keeping this in mind, Table 5 shows that as a road section becomes less hazardous (moving from Scenario 3 to 1), the estimated thresholds allow for the pavement condition to deteriorate further in time (and vice versa; the more hazardous a road section, the sooner a pavement needs to be treated). Table 6 depicts these relationships.

Compared with the thresholds found in literature (Table 7), the safety- and cost-based thresholds presented for the three scenarios (averaged in Table 7) may be somewhat different, in that they allow, in most cases, for the pavement condition to deteriorate relatively further in time. This is expected, given that the one of the objectives in the analysis was to also maximize the
pavement service life. It should be noted here that the thresholds in literature are mostly historical thresholds, or are based on solely expert panels, user opinions, or some cost factor.

**Table 6. Relationships between safety hazard and pavement performance thresholds**

<table>
<thead>
<tr>
<th>Threshold values for:</th>
<th>Safety hazard:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>International roughness index (IRI)</td>
<td>Scenario 1 &gt; Scenario 2 &gt; Scenario 3</td>
</tr>
<tr>
<td>Pavement condition rating (PCR)</td>
<td>Scenario 1 &lt; Scenario 2 &lt; Scenario 3</td>
</tr>
<tr>
<td>Rut depth</td>
<td>Scenario 1 &gt; Scenario 2 &gt; Scenario 3</td>
</tr>
<tr>
<td>Surface deflection</td>
<td>Scenario 1 &gt; Scenario 2 &gt; Scenario 3</td>
</tr>
</tbody>
</table>

Note: Scenarios 1, 2, and 3 correspond to lower, median, and higher accident rates, respectively.

**Table 7. Pavement performance thresholds and service lives found in literature (historical or based on expert/user opinions) Vs. current study findings**

<table>
<thead>
<tr>
<th>Pavement Performance Thresholds</th>
<th>Pavement Service Life (Avg.)</th>
<th>Pavement Service Life (Std.Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IRI (in/mi)</td>
<td>PCR (0-100)</td>
<td>Rut depth (in)</td>
</tr>
<tr>
<td>Flintsch and Zaniewski (1997)</td>
<td>105.0</td>
<td>n/a</td>
</tr>
<tr>
<td>FHWA (1999)</td>
<td>170.0</td>
<td>n/a</td>
</tr>
<tr>
<td>Hicks et al. (2000)</td>
<td>108.6</td>
<td>61.2</td>
</tr>
<tr>
<td>Shafizadeh and Mannering (2003)</td>
<td>170.0</td>
<td>n/a</td>
</tr>
<tr>
<td>Lamptey et al. (2005)</td>
<td>113.1</td>
<td>88.3</td>
</tr>
<tr>
<td>Labi et al. (2005)</td>
<td>73.7</td>
<td>87.9</td>
</tr>
<tr>
<td>Labi et al. (2005)</td>
<td>102.2</td>
<td>94.6</td>
</tr>
<tr>
<td>Current Study Findings</td>
<td>163.9</td>
<td>59.8</td>
</tr>
</tbody>
</table>

- Threshold values with respect to acceptable level of road roughness by users.
- Average values.
- This study validated FHWA's acceptable levels of road roughness.
- Average historical threshold values for interstate roads.
- Average historical threshold values for non-interstate roads.
- Average pavement service life estimated from sample.
- Standard deviation of pavement service life estimated from sample.

As a final point, to the authors' knowledge, the effect of unrecoverable surface deflection on pavement deterioration has not been extensively investigated in the literature (see, Fwa et al., 1997; Anastasopouls, 2009; Anastasopouls et al., 2012c) within the performance analysis.
framework, most likely due to data limitations. In the current research study, surface deflection appears to play a very important role in the pavement performance threshold determination process. And the resulting threshold values depict the effect that traffic (type and volume), temperature and moisture (affecting the pavement structure) have on safety and pavement deterioration. It is therefore demonstrated that surface deflection is statistically correlated with the structural relationship between pavement performance and safety performance of a roadway segment.

5. SUMMARY AND CONCLUSIONS

This paper presents a method to estimate pavement performance thresholds. Building on past research, an estimation method for determining thresholds is demonstrated, through its basis on safety, pavement service live longevity and cost criteria, and utilizes mathematical programming. Four pavement performance indicators are analyzed: the international roughness index, rut depth, pavement condition rating, and surface deflection.

Using data from urban interstates in Indiana, random parameters statistical models are developed to link safety, treatment cost, and pavement service life with pavement condition, performance threshold, road geometry, and traffic and weather characteristics. Given these established relationships, multi-objective optimization and goal programming are used –as one possible approach– to estimate a set of optimal pavement performance thresholds with respect to the 80th, 85th, and 90th percentiles of the most hazardous road sections. The least hazardous, with respect to the corresponding percentile, minimum (to reduce costs affiliated to needlessly frequent pavement treatment-actions) pavement condition is sought.
The safety-based thresholds are found to be independent of the pavement rehabilitation treatment type (and of the pavement type), but depend on an accident-related safety norm, and a number of factors, such as pavement condition, traffic and truck loads, traffic and weather characteristics, and road geometrics. Given some standard (mean/median) values, the average IRI, PCR, RUT, and FWD thresholds for urban interstates are estimated to be 163.9 in/mi, 59.8, 0.34 inches, and 18.9 mils, respectively, and lie within the range of threshold values found in the literature.

This study aims to produce a better understanding of the estimation mechanisms of the performance thresholds of pavement treatments. The estimation results seek to enhance decision-makers’ understanding of how and when preservation should be initiated. However, these results are subject to some limitations inherent in the models and methods used, available data sources, and research scope. For example, future research could include additional criteria (such as agency, user, and vehicle operating costs, environmental, ecological, or other impacts) in the threshold determination process.

Given the complexity of the problem and the limitations of available data, this study should be viewed as an incremental step toward enabling transportation agencies to make better decisions regarding how and when treatments should be initiated, allowing the selection of treatment options that will last the longest. Further avenues for enhancing the methodological reach of this framework exist. For example, the safety functions estimated can be extended to multivariate dimensions to account for severity effects, thereby helping delineate the nature of the safety threshold and not focusing on overall rate alone. This may yield interesting insights especially in terms of behavioral tradeoffs (such as speeding) that can occur with pavement resurfacing.
6. ACKNOWLEDGEMENTS

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7. REFERENCES


Dong, C., Nambisan, S., Richards, S., Ma, Z., 2015. Assessment of the effects of highway geometric design features on the frequency of truck involved crashes using bivariate regression. Transportation Research Part A, 75, 30-41.


Labi, S., Lamptey, G., Konduri, S., Sinha, K., 2005. Analysis of Long-Term Effectiveness of Thin Hot-Mix Asphaltic Concrete Overlay Treatments. Transportation Research Record 1940, 3–12.


